Redefining recruitment and selection processes for responsible AI in pre-employment assessments

Dr Olivia Kyriakidou, The American College of Greece, Greece (okyriakidou@acg.edu)

Introduction

In 2018, the UN laid out its vision for artificial intelligence (AI) that enables algorithmic decision-making, which promotes “ethical, secure and cutting-edge AI”. Specifically, AI can contribute to the realization of the UN’s Sustainable Development Goals, such as advancing gender equity, promoting citizens’ wellbeing, and monitoring social cohesion indicators. To do this, AI needs to be human-centric and committed to the service of the common good.

Implementing AI in recruitment and selection has become highly popular (Leicht-Deobald et al., 2019) as sophisticated AI tools and technologies that use machine learning systems are employed to automate many aspects of decision-making (Budhwar et al., 2022; Yarger et al., 2020). AI tools have have evident advantages as screening and assessment decision-making processes and procedures become fast and efficient (van Esch & Black, 2019). It is perhaps not surprising, however, that the use of AI in recruitment and selection operations, processes and practices (Cheng & Hackett, 2019) has been the subject of a growing body of critical research within work and organization studies (e.g., Ajunwa, 2020; Beer, 2017). Whether articulated through arguments of lacking regulatory measures (Ajunwa, 2020) or “good” employment data, a seemingly ubiquitous rhetorical commitment to the use of AI in recruitment and selection represents not just a problematic HRM discourse, but also a powerful one. Critical research has considered the implications of AI decision-making on employee control, surveillance, ethics and discrimination (Ajunwa, 2020; Beer, 2017; Parry et al., 2016; Mittelstadt et al., 2016). Moreover, it has highlighted how human biases can be inscribed into the code of AI tools sustaining inequalities while assuming a veneer of objectivity (Raghavan et al, 2020). The case of AI recruitment and selection assessments illustrates vividly such inscription. Recruitment AI trained on historical employment data, for example, where mostly males hold management positions, may come to the conclusion that women do not seek management positions and therefore may never present a recruitment job post for a managerial role to women through social media. In such circumstances, the original gender bias will be reified due to the biased data that trained the recruitment algorithm (Devlin, 2017; O'Neil, 2016).

Evolving from this body of work, scholars have called for an understanding of the processes through which AI in recruitment and selection may mask inequality and discrimination, replicate social and organizational inequalities and in some instances even amplify human bias (Ajunwa, 2020; Turner Lee et al., 2019). Moreover, addressing the challenges of AI in recruitment and selection requires redefining our perspectives on established practices as AI affects the design and delivery of recruitment and selection practices. Such a redefining could include: a) an understanding of how AI works in specific HRM processes, b) an understanding of what biases exist and how they can be incorporated into AI systems in specific HRM processes, and c) the development of frameworks for the responsible use of AI in certain HRM processes. Given the impact that AI might have on employment as a whole (Raghavan et al., 2020) and HRM's crucial role in such workplace and societal developments, it is imperative that we develop frameworks that will guide HRM's future practice in this domain. The role of such frameworks is crucial since the uncritical implementation of AI recommendations might perpetuate the biases that are hidden into the code of AI and prevent the application of ethical technology without compromising human fundamental values, such as respect for human rights, prevention of harm, inclusion, fairness, and respect for all.

With this in mind, the objective of the paper is fourfold: a) to focus on a specific HRM process, such as the pre-employment assessments that take place in the recruitment and selection process, b) explore how AI works in pre-employment assessments, c) identify how biases could be incorporated in AI in pre-employment assessments, and d) develop a framework for future work and practice for the development and implementation of ethical AI in pre-employment assessments. In this way, our paper contributes to the development and implementation of ethical AI tools and technologies, maximizing the benefits of AI systems in HRM and especially pre-employment assessments while at the same time preventing their risks.

AI in the recruiting and selection process

The subsequent sections present a review of the AI-enabled tools implemented in recruitment and selection and considered in the relevant studies. Getting an insight of how AI-enabled technologies are implemented in recruitment and selection processes could shed light on the biases and ethical risks that might emerge from their use. This review demonstrates the implementation of AI-enabled tools and practices at each stage of the recruitment and selection process highlighting at the same time the possible biases and risks that may rise at each stage. The stages of the recruitment and selection process that are going to be analyzed are: a) sourcing, b) screening, c) assessment, and d) selection.

The role of AI in the sourcing stage

Our literature review indicates that AI-enabled tools and applications are extensively implemented in the sourcing stage of the recruitment process where organizations seek to identify and attract candidates for their job openings. AI-enabled tools on digital platforms and social media (Jeske & Shultz, 2016) are used by many companies in order to expand their reach to potential applicants by automatically targeting a large number of potential candidates and informing them of their job openings (Bogen, 2019; Hunkenschroer & Luetge, 2022). Nowadays, companies are able to benefit from the same digital marketing and targeted communications tools used by the e-commerce industry (Kim & Scott, 2019). Employers can use AI tools with the aim to microtarget and behaviorally target potential candidates by specifying the general demographic characteristics of the individuals who they would like to view the job opening and apply to the specific job opportunity (Purvis, 2016). In other words, AI tools in digital advertising are used to target the applicants that the company would like to attract. Sourcing is also assisted by the use of AI bots that detect, for example through LinkedIn, both active and passive applicants or search the database of applicant tracking systems in order to bring to light former applicants that they would like to target (van Esch & Black, 2019).

At the same time, AI tools can be used for the purpose of writing attractive job listings and possibly de-bias them from potential gender biases (Lewis, 2018). Text-mining tools are applied in order to assess the job post for keywords that will predict its performance in persuading desirable candidates to apply based on the application and selection results of millions of job listings that determine the appealing characteristics of a job ad in numerous contexts (Pejic-Bach et al., 2020). AI applications can also be used for de-biasing job postings as they can suggest improvements to their wording making them more inclusive (Yarger et al., 2020) for more diverse groups of candidates or customizing them for certain groups (Rąb-Kettler & Lehnervp, 2019).

Mapping of biases in sourcing

Kim and Scott (2019, p. 23) argue that “not informing people of a job opportunity is a highly effective barrier” to putting in an application for that job role. AI-enabled digital advertising and social media tools can severely restrict or considerably broaden the types of individuals who will eventually learn for the existence of a specific job opportunity (Kim, 2020; Levy & Barocas, 2017; Speicher et al., 2018). More specifically, the AI technologies used on digital advertising and job board platforms play a crucial role towards this direction. Companies can use job board platforms to target specific types of candidates with their job opportunities (Datta et al., 2018) as well as social media platforms that display job postings by directing job ads to passive and active jobseekers based on their demographic information and presumed interests (Kim, 2020) excluding at the same time groups of users from receiving certain ads based on the employer’s targeting choices (Speicher et al., 2018). Moreover, job postings are placed on general purpose search engines, websites and mobile applications targeting possible applicants based on their search terms, geographic location, and their shared characteristics or interests using a broad array of digital data that is both granted by the individuals themselves and deduced from their digital presence (Bogen & Rieke, 2018). On such platforms, employers have the opportunity to target specific groups of individuals such as those who had visited in the past the company’s career site (Kim, 2020) or who had begun but not completed an online application form or specify the characteristics of the individuals who are considered suitable to see a certain job listing (Bogen

& Rieke, 2018). In the latter case, the AI-enabled digital advertising platforms promise to target candidates who are forecasted to be similar to the ones the employer wants to attract (Datta et al., 2018).

At the same time, digital advertising platforms use also their own criteria to determine who is eligible to see a job posting. Due to limited advertising space, digital platforms direct specific job postings to specific types of individuals based on their own prediction of the individuals' likelihood to click on the ad or to act in a desirable way, such as to apply for the specific position, an irrespective of the employer's desire to pay (Ali et al., 2019). However, all these AI tools that use optimization techniques to direct ads to certain individuals based on user behavior but not in who could be successful in the role (Bogen, 2019), risk preventing the appearance of job postings to individuals with demographics and implied characteristics that are historically not related to such actions and behaviors. Lambrecht et al. (2018) conducted an experimental putting numerous advertisements for STEM education on Facebook and they discovered that the ads were systematically presented more to men than women, even though the numbers of women exceed those of men on Facebook. As a result, such techniques can reduce the number of individuals from underrepresented groups who will have the opportunity to see specific job postings replicating in this way existing biases and stereotypes in the labor force. Bogen (2019) discovered that jobs posts for supermarket cashier positions on Facebook were directed mostly to women at a percentage of 85%, revealing the sourcing bias in AI-tools that leads to adverse impact.

The role of AI in the screening stage

The screening stage typically includes the review of the applications based on qualifications, soft skills and other capabilities, the rejection of unqualified candidates and the ranking and prioritization of candidates for further consideration. The majority of the studies that explore AI bias in recruitment and selection highlight the use of AI tools and technologies in the early stages of CV screening and job matching. Nowadays, AI tools move beyond the traditional algorithms that use predetermined keywords and phrases to review CVs and compile shortlists and rankings of the most suitable applicants (Bornstein, 2017; Vasconcelos et al., 2018). Applicants' qualifications are specified through chatbots and text mining tools for resumes that search for semantic matches and even machine learning that attempts to predict an applicant's future job performance based on a number of indicators, such as the applicant's tenure, productivity or disciplinary sanctions (Bogen, 2019). After the preliminary screening, AI tools can indicate the job opportunity that best matches the qualifications and profile of specific applicants (Rąb-Kettler & Lehnervp, 2019). In this sense, job applicants may see individualized job recommendations and recruiters or hiring managers may obtain a ranked list of suitable candidates. Even though such screening AI tools are thought to create efficient and streamlined screening processes especially for companies that receive large numbers of applications, rapidly cutting down the candidate pool, there are fears that they might disregard qualified candidates (Persson, 2016). A considerable number of candidates are automatically rejected during this stage by AI-enabled screening tools.

Mapping of biases in screening

Most AI-enabled screening tools and technologies used within the boundaries of an organization take into account and reproduce previous employment decisions mirroring and reproducing employment patterns that reflect prior interpersonal, organizational and societal biases and stereotypes (Vassilopoulou et al., 2022). This illustrates what Conway (1968) in his classic article on software design hinted: that system design closely follows prior organizational context. It may seem, then, that certain rules are delegated to a code-based software, which implements those rules “on the fly”. The problem though is that AI is trained on employment data that may be biased. An algorithm based on historic employment data, for example, would integrate that most managers are male, thereby assuming that women are less interested in management positions. Ozkazanc-Pan (2019) also highlighted the fact that the use of use of employee historical data that create specific desirable employee profiles and traits for hiring, run the risk of recommending the selection of the same employee groups again and again, creating homogeneous organizations (Chamorro-Premuzic et al., 2019) and inhibiting their diversity endeavors.

Natural language processing (NLP) tools may be also used during the screening process and especially when organizations use chatbots to screen job applicants (Nawaz & Gomes, 2020). However, studies have found that NLP tools can swiftly absorb society’s gender and racial biases as they are trained on biased data (Sun et al., 2019). For instance, Sutton et al. (2018) uncovered that NLP tools related African-American names to negative emotions while they associated female names with domestic rather than professional work and technical job roles. Moreover, even though NLP tools have been improved recently (Hirschberg & Manning, 2015), they are still trained on data with limited diversity causing poor performance when the job applicants have different forms of accent and when English is not their first language (Blodgett et al., 2016). This means that NLP tools may misinterpret, put at a disadvantage or even wrongfully reject job applicants who do not conform to the algorithm’s anticipated linguistic patterns

(Hemalatha et al., 2021). The same is true also for the image datasets that are used to train image recognition machine learning algorithms which lack diversity and fail when provided with images from the developing world (Shankar et al., 2017).

After the preliminary screening of the resumes, AI-enabled job matching tools associate job candidates with the right job opportunities and develop a ranked listing of recommendations (Martinez-Gil et al., 2019). However, just like certain applicants are associated with suitable job opportunities, others are screened out from specific opportunities and are not presented to the relevant recruiters and hiring managers. This effect may be due to the way that the recommendation systems of the job matching algorithms operate. Recommendation systems on digital job boards generally depend on two main methods in order to derive their individualized recommendations. The first one is content-based filtering that assesses people's interests, based on what they have already clicked on digital platforms and other behavioral patterns, and display similar content to them. The second one is collaborative filtering that tries to predict people's interests by considering what similar others are interested in (Yang et al., 2017).

Both methods are associated with significant bias challenges. Content-based filtering can reproduce and strengthen people's prior cognitive biases (Atas et al., 2021). For instance, women who doubt about their qualifications and suitability for senior managerial positions may be inclined to click on lower-level job postings even though they have several years of work experience. Such behavior will be picked up by the matching algorithm showing them fewer senior-level job opportunities than they would otherwise be qualified for (Bogen & Rieke, 2018). On the contrary, collaborative filtering may stereotype job applicants due to the behaviors of similar others (Yang et al., 2017). For instance, the matching algorithms may learn that similar women to our female candidate tend to apply for lower-level job roles presenting to her fewer senior management positions even when she clicks on senior management positions herself – not because of her own behavior but because of the behavior of similar others (Bogen & Rieke, 2018).

Lastly, headhunting AI faces the same critical bias challenges as matching AI tools due to their underlying recommendation systems. For example, if a hiring manager has the tendency to click on the profiles of male data scientists, the headhunting algorithm will tend to show him or her more male data scientist profiles, but also other hiring managers looking for relevant roles will receive more recommendations for male data scientists instead of women. In addition, male data scientists will begin to see these job listings at a great rate than women because their profiles do not attract the attention of the hiring managers at the same rate. This means that the relevant headhunting AI tools do not base their recommendations and predictions on parameters of job success but rather on hiring managers or job applicants' behaviors, which in turn may reproduce and strengthen biases and stereotypes in the labor market. Finally, headhunting AI when it gives priority to company fit or likelihood of being hired, may exclude candidates with minimal work experience in similar organizations, despite their qualifications.

The role of AI in the assessment stage

AI assessment tools are used to appraise aptitudes, competencies, skills and personality traits in order to distinguish possible strong performers from a large pool of qualified candidates (Vrontis et al., 2022). Most of them are built on traditional tests and assessments offering "off-the-self" assessments for a wide range of job roles and competencies (Tippins et al., 2021) and attempting to predict generic job performance. On the other hand, there are custom-built assessments for specific organizations and job roles that utilize the organization's current employees' performance data to predict how job applicants compare against them on the same assessments (Polli et al., 2019; Tambe et al., 2019).

Even though assessment AI is not novel in recruitment and selection, recently there has been a significant uptake of structured video interviews analyzed by AI tools that substitute for human interviewers and present the job applicants with a brief collection of preset questions (Fernández-Martínez & Fernández, 2020). Such tools might be used to save time, especially when hiring managers receive large numbers of applications, and standardize the process in order to avoid the intrusion of subjectivism and biases (Blacksmith et al., 2016). In addition, the AI tools do not just assess the content of candidates' responses to the predetermined questions but also analyze evaluate a number of complementary features, such as the candidates' tone of voice, facial expressions and emotions to gain an understanding into their personality characteristics and competencies (Köchling et al., 2020; van Esch & Black, 2019).

Beyond structured video interviews, AI-enabled assessment tools embedded in numerous skill tests, gamified assessments and simulations are utilized to evaluate various candidate cognitive and social traits, such as candidates' risk attitude, persistence or motivation (Chamorro-Premuzic et al., 2016; Tippins et al., 2021). In some cases, the specific characteristics are not predetermined by the organization (Polli et al., 2019; Raghavan et al., 2020) but are specified after the algorithms analyze how the company's best performers complete on these tests and infer the characteristics and variables that are associated with high levels of job performance (Tambe et al., 2019). The data obtained from the assessment of top performers create a success profile for the specific role which the machine learning algorithm uses to predict a candidate's suitability and possible success at the specific job role (Polli et al., 2019).

Finally, AI tools could also be implemented to examine a candidate's digital content in order to create the psychological profile of the job applicant (Chamorro-Premuzic et al., 2017). Using linguistic analyses of the candidates' digital presence, AI tools try to derive the candidates' personality and other significant individual differences and assess their fit with the culture of the hiring company (Vasconcelos et al., 2018).

Mapping of biases in assessment

Assessment tests have a profoundly problematic past and have been characterized as essentially biased against both people of color (Haney, 1982) and people with disabilities (Tippins et al., 2021). The most recent AI-enabled assessment tools put forward analogous concerns about validity, biases, and their impact on recruiters' and hiring managers' decision-making (Hunkenschroer & Luetge, 2022; Illingworth, A.J. 2015). Distinguishing between high and low performers in an organization can frequently mirror subjective and arbitrary performance appraisals or inappropriate structural biases (Hart, 2005; Schoorman, D. (1988). For example, the predictive AI assessment tool developed by Amazon in order to infer patterns in successful CVs submitted to the organization over a 10-year period, manifested significant hiring biases for male and against women applicants, allocating smaller scores to the CVs of women candidates during the ranking process. This was mainly due to the fact that the AI tool was trained mainly on male CVs and current high performing employees, an indication of male domination in the tech industry (Meyer, 2018). Thus, the AI tool penalized female characteristics and unintentionally discriminated against women (Mujtaba & Mahapatra, 2019) as they were underrepresented in current employee groups creating biased training data for the assessment algorithms (Kim, 2017). Moreover, Tambe et al. (2019) stated that high performing employees are difficult to assess, as it is hard to separate the individual from the group in terms of performance assessment.

Video interviewing AI systems also raise serious concerns and on reasonable grounds. Speech recognition algorithms do not perform well on people with different that the expected accents (DiChristofano et al., 2022) and facial recognition algorithms perform poorly when they are applied to faces with darker skin (Buolamwini & Gebru, 2018). Fernández-Martínez and Fernández (2020) also cautioned that AI tools cannot easily recognize different types of emotions as expressed in various cultures consistently disadvantaging certain racial or ethnic groups (Feldman et al., 2019). Video interviewing analysis AI has also been criticized on the grounds of its legitimacy to inform hiring decisions as it uses physical characteristics and facial expressions that are not credibly related to success on the job (Fernández-Martínez & Fernández (2022). In addition, such tools may unfairly disadvantage candidates for visible or speech disabilities (Konopasky, 2021) and give an advantage to others for unrelated and insignificant characteristics, such as exaggerated facial expressions (Bogen & Rieke, 2018). Moreover, considering people's fixed characteristics may breach expectations of dignity and justice (Dattner et al., 2019; Reichel, 2017) preventing candidates to perform at their best capacity. Besides, the implicit assessment of personality is still an unresolved and disputed subject (De Cuyper et al., 2017). As a result, serious consideration is needed for the automated elimination of candidates made by these tools.

The validity and technical soundness of all AI-powered assessment tools is necessary as they need to provide evidence showing their relevance and prediction of job performance (Chamorro-Premuzic et al., 2016). Even though the research evidence regarding the validity of well-established applicant assessment methods is strong, such as job interviews, assessment centers, or aptitude tests, AI tools have not received substantial scientific validation about their ability to predict job performance (Dattner et al., 2019; Raghavan et al., 2020). It is implied therefore that companies may exclude applicants based on inexplicable correlations with unclear causal relationship to job performance (Cappelli, 2019; Kim, 2017). However, it should be highlighted that machine learning technologies allow companies to correlate almost any assessment to some element of job performance indicating that the current validity criteria may not be appropriate to guard against unfair hiring results (Kim, 2017). Beyond validity concerns, such tools are built on theories that mirror specific historical and social patterns discriminating against candidates from diverse backgrounds even with similar competencies and skills (Markus & Kitayama, 1991). AI-enabled assessment tools could unfairly disadvantage and punish job applicants who don't fit a well-established theory, especially those with disabilities (Guo et al., 2020). Besides, the introduction of video games as assessment tools to the selection process may interfere with the applicant's performance adding measurement error (Ryan & Derous, 2019).

A widely used criterion in AI-enabled assessment is "culture fit", defined as the "likelihood that a job candidate will be able to conform and adapt to the core values and collective behaviors that make up an organization" (Rouse, 2014). To obtain job and organizational matching, a number of characteristics are considered as estimates of fit (Bye et al., 2014) even though this is a highly subjective and hard to perform process. However, when assessments of culture fit are used in AI tools and technologies, they may become hard rules excluding rather than creating cultures of inclusion within which candidates 'fit'.

The numerical score assigned to each candidate by many AI assessment tools and the subsequent ranking of candidates based on this score is also of great concern as it can generate the belief that there are considerable differences between applicants when in reality there are just a few, if any

(Accominotti & Tadmon, 2020; Espeland & Stevens, 1988). The problem is especially concerning when the assessment tools are trained on employee performance data which are in many cases of poor quality (Roberson et al., 2007). Such rankings trigger the illusion of statistical accuracy and significant difference that could affect the way recruiters and hiring managers perceive applicants throughout the hiring process.

Moreover, criteria that serve as proxies for group membership could be implicated in AI-enabled assessment biases producing patterns based on flawed motifs of causation (Bîgu & Cernea, 2019). For example, assessing employment gaps as a criterion in hiring might inadvertently influence women jobseekers as they exit the workplace in greater numbers due to caring responsibilities (Ajunwa, 2020). Proxies for "interest" may also be very powerful in reproducing cognitive biases. Hiring algorithms could also optimise the level of salary, bonus and benefits that should be offered to candidates in order to increase their possibility of acceptance. Such recommendations, however, may augment gender or racial pay gaps since HR data include numerous proxies that could be reflected in salary recommendations (Porter & Jones, 2018). The existence of proxies thus permits the discrimination against a protected group but based on legitimate grounds (Bîgu & Cernea, 2019; Fernández-Martínez & Fernández, 2020) and indicates that eliminating identifying variables, such as race or gender, may not deter algorithmic models from mirroring patterns of past bias.

Finally, assessment algorithms tend to segregate individuals into groups, drawing conclusions about how groups behave differently and their common characteristics: an action that perpetuates stereotypes. Assessment algorithms, for example, are based on the traits that differentiate high from low performers within a company (Hart, 2005), outcomes subsequently used to recommend certain applicants for hiring. Such traits, however, even when inferred accurately by the algorithms, may not be causally related to performance and could even be quite random. Taken together, such features may unjustifiably allocate specific applicants, especially people with disabilities (Trewin, 2018) to lower status positions. In addition, the classification of individuals into specific identity categories, such as “male” and “female” and “cisgender” could result in the marginalization of non-binary and transgender people, while race could act as a political classification, signaling a status inequality (Keyes, 2018).

The role of AI in the selection stage

The final selection stage includes in most of the cases the completion of background checks and the negotiation of offer terms. Background checks are commonly used to ascertain the criminal history of the applicants and whether they are authorized to work. AI tools are also used in this stage in order to predict the possible breach of employment policies by job applicants (Cooke et al., 2019) as well as evaluate the elements of the final employment offer in terms of salary, benefits, start date and other information planning for onboarding activities and payroll changes (Sánchez-Monedero et al., 2020). At the final stage of the hiring process, AI tools predict the probability that an applicant will accept a given offer and what the employer could do to increase the chances of accepting the offer. For both candidates and employers, this is a crucial negotiation opportunity.

Mapping of biases in selection

Automated background checks could have an uneven negative impact on women, employees of color and immigrants (Volpone et al., 2015). More specifically, background checks that use social media data are concerning for numerous reasons (Jeske & Shultz, 2016). Firstly, even though it is assumed that an individual's online content is related to their workplace behaviors (Kluemer et al., 2012), van Iddekinge et al. (2016) found no significant relationship between recruiters' assessments of candidates' Facebook data and their job performance. Secondly, social media tools, even the most advanced, cannot analyze and understand the subtle meanings of human communication or discern the intention of the communicators (Cobbe, 2021). Lastly, during background checks, a number of private individual information could be surfaced about the candidate's race, age, disability, sexual orientation, etc. (Dattner et al., 2019) that should not be considered in the selection process.

Moreover, regarding the final employment offer, AI tools could predict what specific offer the applicants are likely to accept as personnel data usually contain abundant proxies for the candidates' socioeconomic status and racial group (Hamilton & Davison, 2021; Vassilopoulou et al., 2022), magnifying the salary gap for women and employees of color. Nevertheless, providing individualized insights into an applicant's pay requirements expands information asymmetry against job applicants at a crucial negotiation point in time (Sánchez-Monedero et al., 2020). AI tools may also undermine laws that prevent employers from discussing applicants' salary history when making salary decisions in order to tackle the pay gap (Mulligan, 2018). However, when employers can predict a candidate's salary history from a number of proxies, they do not have to ask. At the same time, however, these same AI tools allow employers to reflect on their own compensation policies and address possible pay gaps.

Approaches to mitigate bias

We appreciate that mitigating biases in recruitment and selection AI is a complicated, multidimensional and challenging undertaking. Approaching algorithmic decision-making in recruitment and selection as an aggregation of human and non-human actors provides the opportunity to reconceive AI tools by considering who produces them, based on which theories, for which purposes, under what conditions of accountability and for whose benefit (Vassilopoulou et al., 2022). Therefore, any critical commitment to mitigate bias in recruitment and selection AI tools and algorithms should begin with problematizing the aggregation in which AI tools are designed and implemented and centralizing it around the value of moral and ethical responsibility.

To mitigate bias, the human element is based at the heart of the analysis. Jonsen and Ozbilgin's (2014) maturity model is used for workplace interventions which includes the following phases: awareness raising activities for the identification of the challenges, structural remedies, and deep level learning where underlying assumptions are challenged.

Awareness raising starts by recognizing the indisputable relationship between scientism and the implementation of AI tools in HR (Vassilopoulou et al., 2022). The categorization of AI tools in the mind of HR professionals as scientific products based on objective methods guides them towards an unquestionable and uncritical implementation of such tools in their daily practices. Moreover, it might guide them towards uncritically accepting the AI recommendations letting it to affect their decision-making process in a significant manner. Mergen and Ozbilgin (2021) state that to mitigate such biases, individuals should experience a cognitive dissonance and an ethical dilemma about their perceptions and the actuality of the circumstances. Accordingly, the initial step towards mitigating the bias in recruitment and selection AI tools is for HR professionals to tackle this awareness gap and problematize their trust in AI tools as 'rationality carriers' (Cabantous & Gond, 2011). Such an awareness might motivate organizational stakeholders to begin gathering data regarding the goals and intentions of AI tools and their likely consequences for diverse communities.

The significance of self-reflection is of tremendous significance for HR professionals in order to critically scrutinize the application of AI recommendations without probing into who has been or could be excluded. Such reflections could center around their professional identities, their assumptions and their perceptions of what is at issue with the implementation of AI tools and could derive from a number of perspectives that do not align with formal rationality theory integrating the values of efficiency, effectiveness and objectivity with those of equality, diversity, equity and inclusion. Destabilizing formal rationality assumptions requires an open eye and mind to paradoxes, contradictions, and all those unexpected facts that characterize organizational life (Spicer et al., 2009). Awareness could come, for example, from teaching HRM, and especially recruitment and selection, as an evidence-based practice and incorporating training on bias-proofing algorithms in their professional development. Acknowledging the power relationships and organizational norms that could be inscribed in AI tools is crucial for awareness raising as well as the recognition that AI tools do not reflect the pluralism, diversity and sophistication of organizational and societal life. Such acknowledgment could shift HR professionals' focus to the excluded and marginalized individuals in AI recommendation systems. The contribution of HR practitioners in visualizing how AI tools could lead to inclusive organizations is crucial at this point. Finally, their role could be strengthened with extending their existing psychometric knowledge on the fundamentals of machine learning that could facilitate their participation in significant discussions, such as whether the models used deliver meaningful predictions and whether they can be generalized to other samples.

Once a level of awareness is achieved, the second stage of mitigating biases would include the establishment of structures for tackling the identified challenges. This involves the development of governance arrangements around AI tools in recruitment and selection regarding issues of possible unsuitable implementation, bias and other adverse impact effects. First of all, it is recommended that the use of AI tools in recruitment and selection should comply with privacy policies highlighting the need for organizations to protect sensitive personal data and for recruiters to avoid using or predicting private applicant information during the recruitment and selection process (Hunkenschroer & Luetge, 2022). Further, organizations should always inform applicants when they interact with an AI tool (Simbeck, 2019) and be always ready to provide information about the techniques and datasets used by the AI tools and the processes that lead to specific recommendations (Kochling et al., 2020). Moreover, working parties could be established to prepare policies for the use of AI tools in recruitment and selection and oversee their suitable use within the organization (Tambe et al., 2019). Organizations could also develop accountability structures for commissioning, procuring, implementing and adopting policies for AI use.

From a technical perspective, it is crucial that AI tools in recruitment and selection are assessed against criteria that have been established over many decades in the area of testing and assessment regarding the reliability, validity and utility requirement that such tools need to meet. First of all, each tool needs to be based on a strong theory that supports and predicts the relationship between included data, variables and their link to job requirements. For example, no evident theory seems to support the association between certain facial expressions and the necessary KSAOs that are needed for effective job performance. AI tools need to indicate how each measure included reflects a KSAO required to perform the job as indicated by a job analysis

(Morgeson et al., 2020) which is rarely the case with AI tools that scrap various sources for available data (Braun & Kuljanin, 2015). Further, specific conceptual and empirical evidence regarding the validity for the expected inferences and predictor-criterion relationships is required to indicate the strength of the selection process (Oswald et al., 2020). Crucial questions to be considered are: How were data acquired, organized, cleaned, modified and merged? How were missing data addressed? If text mining was used, how was the impact of vocabulary knowing or verbal fluency restrained? How are conflicting applicant data being handled? Could the analysis be accurately replicated by a third party?

The final stage for mitigating bias in AI tools demands deeper level insights. Organizational values such as equality, diversity, inclusion and moral conduct need to inform the design of AI tools. Intersectional data scientist teams (Giang, 2018) with the participation of HR professionals as co-designers might be necessary for revealing implicit assumptions, mitigating against possible biases and ensuring that bias proofing is embedded within the AI tools. For this to happen, HR professionals need training that enables them to realize the relationships between the technical, social, material and HR dimensions of AI design and application.

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