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Sociotechnical imaginaries of social inequality in the design and use of AI recruitment technology

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ABSTRACT

Through interviewing 12 companies in Italy that either design (vendors) or use (clients) AI recruitment technology systems, we explore how these companies perceive their systems to interact with issues of social inequality and how these perceptions, in practice, carry societal impacts. Three sociotechnical imaginaries (Jasanoff and Kim, 2015) were consistently embedded within these companies' visions of this intersection: the third eye, the river, and the car bonnet. Through critically analysing these imaginaries, we find that they exhibit an overriding desire for productivity and talent capture from clients, and a consequential de-prioritisation of addressing social inequality and scrutinising the ways it could be reproduced from both vendors and clients. It demonstrates that the current 'desired' futures, shown by the sociotechnical imaginaries that vendors and clients share for AI recruitment technologies (AI-rec-tech) are really leading us towards an 'undesirable' future of hiring that continues to perpetuate social inequality. This study contributes one of the first pieces of empirical work to simultaneously assess the perceptions of AI-rec-tech vendors' and clients' surrounding social inequality, to shed light on the priorities for design and the motivations for usage, and to reflect upon how these impact society. This is a significant and original contribution to the evolving body of literature on AI-rec-tech in sociology, critical data studies, and communications.

KEYWORDS Artificial intelligence; sociotechnical imaginaries; social inequality; design; technology; recruitment

Introduction

AI recruitment technologies (henceforth AI-rec-tech, following Collett, 2023) can be used at multiple stages of the recruitment pipeline: sourcing, screening, assessment, and selection (Ajunwa and Schlund, 2020; Black and van Esch,

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2020; Raghavan *et al.*, 2020).[1] When sourcing candidates, AI can be used to search for and advertise to desirable candidates, or to edit the advertisements in an attempt to make them less gendered or racialised (Ajunwa and Schlund, 2020). During the screening process, these systems might adopt optical character recognition, which allows the software to scan and search for keywords to match an applicant's qualifications with job requirements (Dickson and Nusair, 2010). Assessments might analyse candidates' behaviours, cognitive traits, personality, skills, or capabilities through multiple-choice tests or gamified exercises, or they might analyse pre-recorded video interviews and rate candidates based on responses, vocal tone, or facial expressions (Ajunwa and Schlund, 2020; Black and van Esch, 2020). Lastly, these technologies can even exploit algorithms that examine a candidate's criminal history or social media to aid with the selection decision (Ajunwa and Schlund, 2020).

It has long been discussed that employers use these technologies within the recruitment process because they are capable of sifting through large volumes of applications; they save time, increase efficiency, and claim to aid companies with the recruitment of retainable employees (Niehueser and Boak, 2020; Raghavan *et al.*, 2020). In addition, some argue that these systems can reduce bias and discrimination through eliminating the unconscious bias of humans by basing decisions on skills and abilities as shown by these objective tests, rather than by subjective human decision-making (Florentine, 2016; Jia *et al.*, 2018; Upadhyay and Khandelwal, 2018; Zhang *et al.*, 2019). However, various academics, researchers, lawyers, and regulators warn that the use of AI in recruitment could lead to unfair or discriminatory treatment of certain groups (Raghavan *et al.*, 2020; Tilmes, 2022; Vassilopoulou *et al.*, 2022). For example, the data used to train these systems might simply reproduce ideas of 'fit' in the workplace (Raub, 2018; Halpin and Smith, 2019) if, say, the training data prompt candidates to be selected who replicate the most successful employees, thereby creating a homogenous environment (Ajunwa and Schlund, 2020). Or the data might exclude people who have disabilities affecting their facial expressions, movement, or speech differences, and this might entrench ableism and worsen outcome disparities in hiring by subsequently ranking them lower on certain tests (Tilmes, 2022).

[1] We follow the OECD definition of AI systems: 'An AI system is a machine-based system that is capable of influencing the environment by making recommendations, predictions or decisions for a given set of objectives. It does so by utilising machine and/or human based inputs to: i) perceive real and/or virtual environments; ii) abstract such perceptions into models manually or automatically; and iii) use model interpretations to formulate options for outcomes' (OECD, 2019, p. 20). These systems use specific techniques, such as natural language processing or machine learning with data gathered through text analysis, speech recognition, or image recognition (Iqbal *et al.*, 2020; Charlwood and Guenole, 2022; Miller, 2022). All companies used AI in some capacity in their systems.

However, much existing work on AI-rec-tech has been based on publicly available data or has presented a more theoretical analysis (Drage and Mackereth, 2022). For example, some have analysed these systems from a socio-legal perspective, concluding that these systems might struggle to meet legal standards (Sanchez-Monedero, Dencik and Edwards, 2020), or from an ethical standpoint, pointing out that human rights standards should be further embedded into these systems (Hunkenschroer and Kriebitz, 2023).

While this research has been crucial for mapping the field, it is vital that empirical work focuses on the design, use, and impacts of this technology. Until now, 'we know relatively little about the practical entanglement of ADS [automated decision systems] and recruiting' (Sloane, 2023, p. 3). As many scholars have pointed out, the current lack of empirical work makes it difficult to thoroughly reflect upon these systems regarding their impacts, but this work is crucial (Stone and Dulebohn, 2013; Tambe, Cappelli and Yakubovich, 2019; Köchling and Wehner, 2020). Currently, no research has explored how key stakeholders—such as vendors and clients—perceive issues of social inequality in relation to their design and use of the systems.[2] It is vital to explore this issue so that we might consider in greater depth the potential social implications of these technologies. Moreover, we must consider both stakeholders within research, because of their joint, significant influence upon how these tools impact hiring practices.

With an interest in rectifying this gap, we interviewed 12 companies in Italy that design AI-rec-tech (vendors) or use it for hiring (clients). This lays the groundwork for further research on these topics, and shows, for the first time, how AI-rec-tech is both designed and used in relation to social phenomena, as well as how these perceptions carry potential downstream impacts. This is particularly important within the Italian context, because of the widespread use of AI within the country and the evident pro-innovation approach to AI.

In 2022, Italy was third globally behind India and China in terms of the proportion of companies deploying AI (IBM, 2022). But despite this widespread use of AI, AI-rec-tech has garnered little attention in Italy within academia or otherwise, excepting the recent overview of its legal implications (Bordoni, 2023). Moreover, the Italian AI strategy—first published in 2020 and then again in 2021—puts forward 24 policy initiatives. It is clear, within this strategy, that the '[g]overnment and the largest industrial actors are aware of the competitive edge that AI adoption can provide' (Saracco, 2022, p. 1). Therefore, like many of the

[2] Social inequality in AI relates to the system's ability to distribute, maintain, or perpetuate power relations between social groups who have historically differed in their access to resources and opportunities (Burrell and Fourcade, 2021).

national AI strategies of EU countries, the strategy strongly emphasises the importance of increasing innovation, education, and research around AI, along with seeking the benefits for productivity. In addition, the strategy was produced by a working group made up of academic experts, and 8 out of 9 members of this group were computer scientists (Saracco, 2022). The Italian government has failed to involve scholars from the humanities and social sciences, or members of the public, in shaping policy on AI development and deployment. There has been less focus on the social implications of AI and more prioritisation of innovative and technical expertise (Foffano, Scantamburlo and Cortés, 2023).

It is therefore imperative that more attention is paid to the social implications of AI technology in Italy. The country has long experienced high rates of youth unemployment, unequal gender and racial participation in the labour market, and a prominent employment and digital divide (particularly between the North and South). However, there is little attention being paid to the impact of AI and social disparities (Sartori, 2006; Boca and Giraldo, 2013; Di Pietro, 2021). It is for these reasons that we have chosen to study the Italian context; as the technical perspective has so far prevailed, we aim to shed light on the social dimension of AI-rec-tech, as an example of the potential implications it can carry when inequality is not considered from a social science perspective within design or use.

Overall, this paper argues that there are three sociotechnical imaginaries (Jasanoff and Kim, 2009, 2015) that demonstrate how AI-rec-tech vendors and clients perceive these systems in relation to social inequality: (1) the third eye: AI-rec-tech is a neutral assessor, superior to humans who display cognitive biases; (2) the river: the development of these systems is market-driven and their use inevitable owing to the competitivity value from cost-saving and talent capture; (3) the car bonnet: vendors and clients don’t fully perceive this relation at all because of a lack of understanding about how the systems work under the hood. In turn, we critically analyse these imaginaries to consider how they might play out in practice. From evaluating each, we find that these imaginaries exhibit an overriding desire for productivity and talent capture and a consequential de-prioritisation of addressing social inequality. While this is not necessarily surprising—particularly within the Italian context, or, indeed, within any other starkly pro-innovation country as has been shown in other works (Hoffmann, 2019; Le Bui and Noble, 2020; Crawford, 2021)—this paper provides evidence and nuance to what is behind these views and how they relate to the design and use of AI-rec-tech, and, in addition, it discusses the potential implications. It demonstrates that the current ‘desired’ futures, shown by the sociotechnical imaginaries that vendors and clients share for AI-rec-tech, are really leading us towards an 'undesirable' future of hiring that continues to perpetuate social inequality.

This paper sits within an evolving body of literature within sociology and communications. Empirical data have started to emerge in relation to how AI-rec-tech vendors and clients justify system usage by arguments that existing practices are biased and technology is a more objective solution (Dencik and Stevens, 2021), and how employers use these systems at various points in the recruitment pipeline to make their work more efficient (Li *et al.*, 2021; Sloane, 2023). However, this piece goes a step further by showing how both clients and vendors have an aligned narrative surrounding AI-rec-tech and its relation to social inequality and, therefore, both design and use are likely to reinforce negative impacts from these technologies. Therefore, this work also contributes to broader literature within critical data studies, sociology, and science and technology studies surrounding the potential and actual societal implications of technological systems—including AI—regarding inequality and discrimination in relation to race, gender, class, and other protected characteristics (Eubanks, 2017; Noble, 2018; Agrawal, Gans and Goldfarb, 2019; Broussard, 2023). While we cannot assert the impacts directly, owing to lack of access to this kind of data, in this paper, we discuss the potential implications. Importantly, this leaves a legacy for future work to consider this issue further. Moreover, this paper contributes to literature that utilises sociotechnical imaginaries to analyse narratives in relation to technological design and use (Graf and Sonnberger, 2020; Sörum and Fuentes, 2023), as well as including the novel terms 'the third eye', 'the river', and 'the car bonnet', which can be used in future work to capture these technological visions.

Sociotechnical imaginaries

To investigate how the design or use of these systems intersect with issues of social inequality, we use the lens of sociotechnical imaginaries. Jasanoff and Kim (2015) define sociotechnical imaginaries as 'collectively held, institutionally stabilised, and publicly performed visions of desirable futures, animated by shared understandings of forms of social life and social order attainable through, and supportive of, advances in science and technology' (pp. 4–5). It is this focus on 'collective', 'institutionally stabilised', 'desired futures' that uniquely enables sociotechnical imaginaries—as opposed to just referencing narratives or discourses—to aid our exploration of how social inequality is considered in practice within the design and use of AI-rec-tech. Overall, it provides us with a vocabulary to demonstrate the collective perceptions of vendors and clients visually, and to explore these perceptions further.[3] In addition, it offers long-lasting symbols of the companies' visions of social inequality. While sociotechnical imaginaries denote a future that is desired, we show by critically analysing these imaginaries that, in some cases, they should instead be seen as undesirable, not just as imaginaries but as realities.

Overall, sociotechnical imaginaries enables us to consider what ideologies shape the design and use of AI-rec-tech (Preece, Whittaker and Janes, 2022). Furthermore, it discerns the social arrangements or rearrangements they support, whether desirable or undesirable (Graf and Sonnberger, 2020; Sörum and Fuentes, 2023). As Sartori and Theodorou (2022) discuss, technology is a social practice, and therefore, analysing the 'dominant narratives' will reflect organising visions for society and reveal more tangible signs of social, economic, and political inequalities.

Three sociotechnical imaginaries were explicitly mentioned in at least one interview, and, we argue, were consistently and symbolically implied throughout interviews across vendors and clients. These imaginaries are our interpretations of how companies perceive their systems in relation to social inequalities. In one case, the imaginary represents a desired vision for the present and future role of the technology (the third eye); in the two other cases, the imaginaries shed light on the reality of how AI-rec-tech interacts with and impacts issues of social inequality, and, therefore, showcase an undesirable future towards which we are moving (the river, the car bonnet).

Sample and methods

The sample consists of 12 companies based in Italy. This was made up of 7 companies that design and disseminate AI-rec-tech (vendors) and 5 companies that buy and implement AI-rec-tech (clients). All companies and participants are anonymised within the sample. While this might not seem like a large sample size, as Collett (2023) points out, qualitative researchers attempting to research the technology industry often go through 'the hustle': the struggle to access research settings of participants in the face of resistance. We approached 48 companies in Italy and had a 25% success rate. However, we also queried 20 vendor companies in the US and UK and didn't get a single response. This low response rate in the US and UK dictated our research design, as we were unable to do a comparison between Italy and the US/UK. This also demonstrated to us the opacity of this industry, particularly in the US and UK. However, it was valuable

[3] The data are used as aggregate in these imaginaries because we found that the same themes emerged from both vendor and client companies.

Table 1. Companies and participants.

Company pseudonym	Participant	Participant role
Vendor 1	Vendor 1 P1	CEO
(CV screening and search engine,	Vendor 1 P2	Engineer and Data Scientist
resume redaction, job matching)	Vendor 1 P3	Engineer and Data Scientist
Vendor 2 (Video analysis and job matching)	Vendor 2 P1	CEO
Vendor 3 (Video analysis)	Vendor 3 P1	CEO
Vendor 4 (Video analysis and screening)	Vendor 4 P1	CEO
Vendor 5 (CV screening, ATS, candidate matching to job description)	Vendor 5 P1	Development Director
Vendor 6 (Skills assessment and candidate matching to job advertisements or descriptions)	Vendor 6 P1	CEO
Vendor 7	Vendor 7 P1	Engineer and Data Scientist
(CV screening and candidate matching	Vendor 7 P2	Project Manager
to job description)	Vendor 7 P3	Finance Director
Client 1	Client 1 P1	Managing Director
Client 2	Client 2 P1	CEO
Client 3	Client 3 P1	CEO
Client 4	Client 4 P1	HR Director
	Client 4 P2	HR Director
Client 5	Client 5 P1	CEO

for us to focus on the Italian context singularly, to take a deeper dive into the narratives and trends within this country.

Over these 12 companies, we conducted interviews with 17 people: 11 people from vendor companies, and 6 people from client companies. Participants occupied a mixture of roles, but usually were in leadership positions. Gillespie (2014) positions algorithmic systems as 'knowledge machines' that capture the thoughts and ideas of a select few individuals. In our case, leaders were the key people responsible for directing and enacting the visions for design and use within the organisations.

Table 1 describes the vendor and client companies, provides their pseudonyms, outlines the type of technology they offer, and summarises the roles of the interviewees.[4] Vendor companies are referred to as 'Vendor 1' or 'Client 1' and are organised numerically. Participants, by company, are labelled as P1 (standing for participant one), then ordered upwards numerically. In a few

[4] In some cases, the titles of roles have been changed for anonymity but maintain the type of role.

cases, companies both made and used their own system. In these cases, we have labelled the company as a vendor.

These systems span sourcing, screening, and assessment AI-rec-tech. However, as can be seen in the findings, aspects of functionality between systems were similar. This also made it suitable for us to aggregate the data. Vendors and clients were generally found to perceive these systems in an aligned rather than contrasting way regarding issues of social inequality, another reason why we decided to use the data as aggregate.

As demonstrated in Table 1, some of these technologies were CV screening systems. These generally extracted text, categorised this information into personal data (name, age, nationality, phone, job titles, and skills), and then matched the data to a job description and/or skills profile, or alternatively put these data in a database for the recruiter to search. Other companies allowed candidates to record video interviews that were then analysed for micro-expressions or keywords. These can be either matched to job openings or analysed against the job description for a particular role. Alternatively, it might be that the candidate could take an assessment to see whether their results align with the skills selected by the employer.

Qualitative interviews took place from March to May 2023 on Microsoft Teams. All interviews were recorded and used the inbuilt transcription service. These transcriptions were then downloaded and translated either by the researchers or on DeepL. All participants were aware of this process and signed a consent form prior to interviews agreeing to this process, having read a detailed information sheet about the study. Interviews lasted between 30 and 60 minutes and were semi-structured. We tried to remain flexible with our questions to ensure that we were responding to the interviewees (Hesse-Biber and Leavy, 2007). The questions were broad but helped us to discern the prominent narratives of vendors and clients, as well as their perceptions around how their systems interacted with social inequality.

For vendors:

1. General:
   - Can you give a brief overview of how your system works (for hiring)?
2. AI:
   - What elements of AI does the system use? How are you defining AI?
3. Client motivations:
   - Why are clients interested in purchasing your technologies?
4. Design:
   - How do you design the system to meet these motivations, and can you give examples of how it has met them?
   - What are your priorities when designing the system?

5. Addressing inequality:
   - Does the system address inequalities in hiring and the workplace more generally?

For clients:

1. Client motivations:
   - What are the main reasons you use AI systems in hiring?
2. AI:
   - What elements of AI does the system use? How are you defining AI?
3. Employee perceptions:
   - Has the system fulfilled your hopes and expectations? Why or why not? Can you give some examples?
4. Addressing inequality:
   - Does the system address inequalities in hiring and the workplace more generally?

Thematic analysis was carried out through coding and classifying the data. This analysis allowed us to identify themes, patterns, and relationships (Lapadat, 2010). Braun and Clarke (2006) advocate that we must admit the active role of the researcher who identifies these patterns. They argue that a theme captures something important about the data in relation to the research question and patterns within the dataset. This constructionist method is also suitable for examining the individual and collectively constructed meaning of concepts (James and Busher, 2009) through exploring the origin of the deeper realities, meanings, and experiences of these participants.

The third eye

Vendor 3 P1 told us that these systems 'bring a third eye into your business evaluations'. In certain religions such as Hinduism and Buddhism, a third eye symbolises heightened intuition, wisdom, and insight that goes beyond human perception (Cavendish, 1970). Therefore, the 'third eye' summarises the first way in which these companies perceived AI-rec-tech to interact with issues of social inequality: AI-rec-tech promotes social equality through its ability to be less biased than humans in the context of hiring.

In contrast to AI-rec-tech, humans were perceived to be beset with biases, while these systems were seen not to be influenced by the discriminatory eye of the recruiter. We found this perception consistently across both vendors and clients. Client 3 P1, when asked whether it is the employers who discriminate rather than the AI-rec-tech, responded '[f]rom my point of view, yes'. Client 4 P1 also assured us that AI 'certainly can help [. . .] to make it fairer from the recruitment point of view [. . .] maybe to eliminate some bias'.[5] Client 5 P1 also argued, 'Today the recruiter, when he goes for the interview, can have that bad day. They can, that is, have a very subjective assessment, often, the recruiter'.

In practice, this 'third eye' was perceived to be enacted through two technical mechanisms: by blinding or redacting CVs and by assessing 'soft skills' of candidates. Blinding CVs was a common design technique used to avoid subjective human perception or a tendency to prefer people like the recruiter or the team. Vendor 1 P1 explained that they redacted resumes, which put blocks to obscure information. This meant that the recruiter could share the CV with a colleague without showing sensitive information such as name, age, gender, nationality, and photo, and that when screening the CV, this information is not considered. This means that 'I can't provide a scoring that favours a man over a woman' (Vendor 1 P1). Client 5 P1 also argued that when they use the system, 'The machine is not trained to make that distinction', but rather, 'It is the recruiter who may or may not discriminate'. Vendor 6 P1 also explained to us, 'We have removed all that potentially discriminatory data, therefore [we are] not asking for age, gender, nationality, political, religious beliefs, sexual orientation'.

In terms of assessing soft skills, measuring qualities such as emotional aptitude or confidence was perceived to level the playing field, rather than assessing hard skills, which companies argued could act as a proxy for societal inequality, for example, differences in education influenced by class structures. Client 5 P1 explained that after an ad is placed, the machine provides them with 'a ranking from the best to the least good [. . .] based on my job ad. So, what do I put in the job ad? I look for an accountant who has experience, so he knows how to use the techniques. I also put things that no other portal does [. . .] if I want to find soft skills'. This was also seen to eliminate the human instinct to mirror the demographic characteristics of past successful candidates, focusing instead on skills.

Vendor 6 P1 also described their focus on soft skills in place of other indicators, and how this technique reduces biases: 'We have added a part dedicated to soft skills'. They told us about how the soft skills, of which there are about 30, are ranked from 1 to 10 based on a candidate's self-assessment before they're matched and ranked with those skills the client desires. They continue by explaining that 'this problem [bias] doesn't exist by default, precisely because we only provide skills' (Vendor 6 P1). There seemed to be an assumption that these systems, and the data within, were not capable of discriminating.

[5] Vendors and clients often used terms such as 'bias' when asked about issues of social inequality, hinting that they saw these fixes through a 'technical' lens rather than primarily a social one.

Client 5 P1 declared that ‘the machine cannot discriminate because it has not been told to discriminate’. Likewise, Vendor 7 P1 stated that ‘the data does not discriminate’.

Therefore, the third eye imaginary captures the desired vision for the technology to act as a more objective system in hiring contexts, particularly in comparison to humans. Its ability to promote social equality was through ignoring factors that could be influenced by inequalities (hard skills) and through redacting details on CVs that could influence the judgment of recruiters.

Blinding or redacting CVs and assessing ‘soft skills’ of candidates are design mechanisms that were perceived to enable AI-rec-tech to be a ‘third eye’ in the recruitment process. However, there are two crucial flaws in the ability of this design to promote social equality in practice. We can see that vendors even point out these flaws, perhaps without realising that it contradicts their own imaginary of the desirable future for AI-rec-tech in the hiring sphere.

First, there are crucial factors regarding the relationship between skills and background left unconsidered. It is likely that there will still be a level of hard skills assessment, particularly for some jobs, and this doesn’t consider how social inequality will feed into disparities in qualifications. While blinding or redacting CVs might mean that name or gender aren’t used within the algorithm, or aren’t seen by the recruiter, it doesn’t change the fact that certain hard skills will be required for some jobs, and some people still have an increased chance of obtaining better grades, studying STEM subjects, or going to more prestigious universities. These people will have a better chance of being ranked more highly by the algorithm. We know that, in Italy, for example, in STEM undergraduate degrees, while females are slightly outperforming males in biology, males outperform females in mathematics, physics, chemistry, and computer science in terms of both grades and completion rate (Priulla, D’Angelo and Attanasio, 2021). In support of this trend, Vendor 7 P1 explained that—in their experience—data scientists who are selected for jobs are 95% men, not because women can’t do that job, but because 95% of data science graduates are men: ‘I simply treat everyone, independently of age, gender, religion [. . .] I see what the skills and experience tell me’.

Vendors also do not consider that so-called soft skills and behaviours might also be proxies for social inequalities (Biesta, 2015; Goyette, 2017). A person’s emotional intelligence, confidence, risk appetite, and vocabulary are likely linked to their background, education, and the influence of their social peers. Moreover, it is likely that this kind of skill development is influenced by the norms within gender and racial structures within society (Thorne, 1993; Evans and Davies, 2000). However, the vendors perceive these factors to be neutral measures that allow AI-rec-tech to be a ‘third eye’.

Therefore, these design elements do not consider how social inequalities contribute to skill differences. Skills are proxies for social similarities and are 'synonymous with the assessments of the likelihood that a candidate can "do the job". In short, fit is skill' (Coverdill and Finlay, 1998, p. 107). This sheds light on the fact that redacting the CV to exclude demographics or altering the system to measure skills directly will—in most cases—not change the outcome or address social inequalities in practice. It is likely that assessing for certain skills, whether so-called soft or hard skills, might still result in trends along gender or racial lines, because of wider structural inequalities in society along these lines.

The measurement of skills was often presented as a way of encouraging social inequality through capturing those who have developed skills, regardless of background. While it might indeed do this in rare cases, for example where someone has self-taught, it was also clear that skill measurement was largely about talent capture. This does not aim to address social inequality as such, and as shown above likely does not do this in practice, but rather its aim is to find the best-suited candidates for the job. Clients were, indeed, explicit about their desire for systems that showed them the most suitable candidates in terms of skills: 'We know that, in the sales area, in the management area, certain traits work. Whether they are men or women doesn't matter' (Client 2 P1). Vendors, also performance driven, were motivated to provide this for their clients. They strived to help client companies create job advertisements that attract the best candidates and aim to 'support recruiters in finding the best match of candidates in the database against the advertisement that the company has published at the time' (Vendor 1 P1). Overall, then, when assessing the relations between these industry actors, this design aims to aid clients with talent capture, rather than being a well-considered mechanism for addressing social inequality.

Second, vendors do not consider that humans are still involved in the most crucial parts of the hiring process. Humans still decide what it means to be a 'successful' candidate (Raub, 2018), through either selecting soft skills or designing the profile of their ideal candidate, which could well 'clone' their best people, especially if it is trained on data from their top performers (Ajunwa and Schlund, 2020). As one of the vendors said, they tell their clients to 'go and select 12 soft skills from those, go and select the ones you are most interested in' (Vendor 3 P1). Humans are the ones, ultimately, who decide how the system is designed, how the data are selected and used, and how and why targets are set (Sloane, 2019).

Therefore, anonymising or redacting can exclude human subjectivity only to a certain extent. While the imaginary of the 'third eye' criticises human perception as being biased, these systems still rely on humans to design their criteria and, more importantly, these systems are so often positioned as being a 'support' for the human decision (Harris, 2018), not a replacement. Vendor 5 P1 clarified that their system is '[t]echnological support in aid of the person, not technology in place of the person'. Vendor 6 P1 also emphasised, 'Artificial intelligence must be something that helps us in the doing of our activities; it shouldn't be a replacement'. Vendor 2 P1 similarly underlined, 'We are not going to replace them [the recruiters], because the final choice is always made by the company'. This sentiment resonated with the answer of clients as well. Client 3 P1 believed these systems are 'an aid' because they are more efficient and faster, but 'the human factor has to intervene to understand that at the level of values and the person you are looking for'. And Client 5 P1 talked about how 'the algorithm does not replace the selector [. . .], the selector always has the last word'.

The alignment between vendors and clients is clear: although some measures are taken to blind the recruiters to demographic details with the aim of reducing bias and promoting social inequality, the industry actors are still motivated to leave the final decision with the client, so they can select the person they perceive to be most suited to the role. It is likely, therefore, that human biases of subjectivity and selecting those with similar backgrounds and values prevails with this design and use of AI-rec-tech (Raghavan *et al.*, 2020; Sanchez-Monedero, Dencik and Edwards, 2020).

The river

The 'river' summarises the second way in which these companies perceived AI-rec-tech to interact with issues of social inequality: AI-rec-tech use and development is inevitable and market-driven and therefore, they cannot control its use and impact on social inequalities. Client 5 P1 brought this imaginary to light, telling us: 'Technology is a river that flows [. . .] you have to do what you can do to stem it better, direct it a little, but the important thing is that there is no blocking of what will happen'.

AI-rec-tech was seen to be the result of a fast-changing economic market, over which vendors and clients had little influence. It has previously been recognised that clients' motivation to buy AI-rec-tech lies in its ability to enhance productivity, speed up repetitive work, and reduce costs (Bauer *et al.*, 2011; Köchling and Wehner, 2020). When L'Oréal used an AI-enabled screening tool to review resumes more efficiently, they said it shortened their review time by 90%, from 40 minutes to 4 minutes per resume (Black and van Esch, 2020), and according to Somen Mondal, CEO of Ideal Corp, AI hiring software reduced the firm's recruitment costs by 71% (Jia *et al.*, 2018). Additionally, if hires are more suited to the role and better retained, this saves the company money on hiring and training a new employee (Ryu, 2019).

As ‘the river’ imaginary symbolises, many vendors and clients perceived AI-rec-tech systems to be related to uncontrollable market-driven competition. Many companies perceived these technologies as necessary for competitive advantage; there is a war for talent, so this is now a top strategic priority for leaders (Nocker and Sena, 2019). Employers often feel they don’t have a choice but to use these to stay competitive (Raghavan *et al.*, 2020) and to manage large volumes of data (Saracco, 2022). As Vendor 2 P1 described: ‘You have to learn to use these tools to keep up with the times and not lag behind’. These systems are used so widely, therefore, because they’re seen to be core to competitive advantage. Client 3 P1 perfectly summarised this idea: ‘There is no doubt that it is a system that greatly simplifies the recruiter’s work because it basically reduces both the time and cost of the entire recruiting process, in this case minimising manual labour’. Of course, this is a desirable imaginary for vendors, who profit from this market pressure, and for employers, who see these systems as finding them the best talent, as well as saving them time and money.

In some of the companies, this inevitability of use was almost used as a justification for a lack of thought about how these systems might intersect with issues of social inequality. Some participants did not indicate that they’d questioned who was included in their training datasets, what the data might reflect, or how issues of social inequality might be captured or perpetuated within the design of the algorithms. When we asked Client 2 P1, for example, about how they ensure their system doesn’t perpetuate social inequalities, they responded by saying, ‘We have actually not honestly asked ourselves this question’. Similarly, within companies that designed or used video or voice analysis, participants were asked about how this might affect someone who has another accent or a facial tic. One company claimed that they ‘haven’t even trained the algorithm on this one’ (Vendor 4 P1).

This illuminates a de-prioritisation of social inequality and represents the shirking of responsibility for the impact of these systems, placing the explanation for usage of these systems on an inevitability that emerges from market competition (Wood and Lehdonvirta, 2022), which itself is used to provide an explanation for de-prioritising issues of social inequality. It was rare for clients to talk about their motivation for usage to be related to addressing social inequality. For example, Client 2 P1 admitted that they didn’t buy this tool with bias in mind, but actually rather they were more interested in speeding things up: ‘Now we have chosen this, actually, for a very simple reason which is the reason of speed [. . .] we move large numbers because sales, compared to other placements, moves massive numbers of resources and so it was important for us to have a tool that was quite fast’.

When asked why their clients purchase their systems, vendors echoed these views. Vendor 3 P1 expressed that today recruitment is 'data driven' and these systems provide these data, while keeping costs low. Clients 'want to do it at a very low cost per person which allows [them] to do a 300- to 400-person first phase' and in addition, they say these systems are 'absolutely a time saver' because they bring forward the stage of matching the people who are compatible with the required skills (Vendor 3 P1). Vendors therefore aimed to provide tools that would meet the market-driven desires of clients. For example, Vendor 2 P1 shared with us that 'the start-up was born out of a very specific need, which is the problem [. . .] the curriculum fails in some way to highlight what the qualities of people are.' They continued to tell us about how, during an internship at a recruitment agency, they 'realised how much time was actually wasted skimming through all the resumes' and then, when the candidates were interviewed, 'often the CV did not correspond to what was, let's say, the real person'. It was a response to a market need and one that is becoming increasingly realised.

Client companies were evidently motivated by saving time and money to stay competitive, and vendor companies were motivated by catering to these needs to stay competitive in their own market. This imaginary therefore demonstrates the main motivation for design and use centres around productivity, and that, subsequently, addressing social inequality was de-prioritised. Without social equality being a priority within the design and use of AI systems that impact people's livelihoods, there is very little chance that, in practice, these systems will have positive societal implications.

The car bonnet

The 'car bonnet' summarises the third way in which these vendors and clients perceived AI-rec-tech to interact with issues of social inequality: once the car bonnet is lifted there is a lack of understanding from employees at vendor and client companies about how AI-rec-tech works to reduce social inequalities. This viewpoint echoes and consolidates the imaginary above by demonstrating the lack of understanding of both vendor and client companies about the way the systems work and therefore the potential implications. Moreover, it is a desirable future for these companies, who might use this lack of understanding to plead ignorance or to shirk responsibility for any negative impacts.

During interviews, it was evident that many participants didn't understand how these systems functioned in terms of considering social inequalities. In some cases, companies were explicit about this lack of understanding. Vendor 1 P1 discussed that there is hype around these systems, but also 'many issues of security, privacy, and regulatory compliance that are not taken into account due to lack of knowledge of what is behind the scenes, i.e., they look at the casing, the car, but what is under the bonnet they know nothing about it'. Moreover, 'The lack of knowledge always generates . . . that is, knowledge of how systems work and therefore of being able to govern them still generates concern. And actually, nobody knows how these artificial intelligence systems really work inside' (Client 1 P1).

Other participants had their ignorance revealed. For example, many participants argued that the systems are more objective because humans might 'miss out on a lot of information' and a 'computer is better able to go and select profiles that have certain skills quickly' (Client 4 P2). Or they might claim that 'the system is absolutely, totally objective, i.e., it goes looking for things and pulls them out' (Vendor 2 P1). However, when asked to explain why, they could not explain it further. For example, Vendor 4 P1, when asked about whether the system was discriminatory, said that there are 'technicians, not like me, the people who have to go over the code'. He also clarified that the 'technology is partly developed by us, partly external'. When asked what type of artificial intelligence they use, he responded by asking what we meant. We clarified by asking, for example, did they use machine learning, and if so, what type? Supervised learning? Unsupervised learning? He told us they did use machine learning, adding that if he needed to be more specific, 'I probably couldn't give you answers' (Vendor 4 P1), because his data scientists were the ones who understood this more. This was not due to any restriction on providing us with information, but due to a lack of knowledge.

When it came to considering how appearance might be measured in a video, multiple companies were unable to explain to us why or how this worked in a way that didn't perpetuate biases and discrimination. For example, Vendor 2 P1 explained that the AI can ignore factors such as facial tics when analysing the video: 'Some [facial] tic, ok? For example, I don't know, the person moving their forehead or the person moving their eyes a certain way [. . .] it [the AI] perceives that they're there, but it's not interested in them, in the sense that what we're looking for are specific to the person, not the person's behaviour'. But when pushed on this issue and how it might consider particular movements, or lack of movements, and how these movements might relate to minority or vulnerable groups, they paused, and responded: 'As I said before, it goes looking for what you ask it to look for, so if I ask it to look for that specific thing, ok, you see 50 others, but those 50 others don't interest you'. Again, this demonstrated a lack of understanding or scrutiny about how this design could impact certain groups, for example, people who are neurodiverse or those on the autism spectrum.

This lack of understanding about how these systems technically work was linked to miscommunication and lack of transparency from vendors, too. Even if they do understand it, they might not be transparent about it. Vendor 3 P1, when asked about how they would not discriminate against a candidate if they had autism or a facial tic, described that they 'only use the transcript as data and therefore this allows that audio and video for us to change absolutely nothing. That is, to us this face tells us nothing, the person's ethnicity tells us nothing, the person's first and last name tells us nothing' and because the emotion analysis is done by sentiment analysis of the text, then this means that 'if you have an accent, you stutter, it doesn't change for us. Simple as that'. However, when asked more about this, they admitted that 'in truth, we do an emotional analysis from the audio'.

The lack of understanding captured in the imaginary of the car bonnet is caused by a lack—or perhaps in some cases a purposeful debt—of information between those in technical and leadership roles within companies, and/or between vendors and clients. Again, this demonstrates that the priority of these companies is not to address social inequality. If it were, these companies would attempt to be more transparent, communicative, and collaborative, so that a wider range of stakeholders could analyse the consequences of these systems. In practice, then, the system is blindly followed without understanding of how it works and, therefore, how it might be perpetuating social inequalities, meaning it is unlikely to promote positive social implications.

Generally, AI systems often remain opaque to their users; they communicate no real-time decision-making mechanisms and there is a lack of information, meaning people struggle to understand why they produce a particular outcome (Sanchez-Monedero, Dencik and Edwards, 2020; Sartori and Theodorou, 2022). This could be due to intentional secrecy (guarded as valuable intellectual property) or technical illiteracy (even if they do share them, researchers and users cannot understand them) (Christin, 2020). But as noted by Köchling and Wehner (2020), it is problematic if companies implement algorithms without being aware of the possible negative consequences. Some argue that it might be too complex and therefore impractical to step through every input to decision that a system makes (Charlwood and Guenole, 2022), or it might risk exposing private information (Thelwall, 2018). However, it is important to have transparency within and between stakeholders including vendors, clients, regulators, auditors, candidates, academics, and users so that these systems can be considered in relation to social impact and inequalities. When it's unclear how AI works it is harder to challenge it, particularly for jobseekers who can't effectively judge whether discriminatory practices might have been part of the hiring process (Sanchez-Monedero, Dencik and Edwards, 2020) and it takes power away from those most affected by these systems. We see the consequences of this phenomenon, as candidates are generally found to harbour feelings of scepticism towards these technologies in comparison to human interviewers (Lee, 2018; Schick and Fischer, 2021).

Scrutinising these systems through collaboration is particularly critical when iterations of AI-rec-tech likely pose more dangers to vulnerable groups. Many scholars and activists have opposed the use of facial recognition in these systems and called for its removal (Crawford *et al.*, 2019). Whether people's facial expressions, voices, language, and appearance can indicate their job competence (Barrett *et al.*, 2019) has been widely questioned. Moreover, facial recognition has been found to have higher error rates for people of colour (Buolamwini and Gebru, 2018) and has been criticised in relation to how it might misinterpret facial expressions of people with disabilities such as cleft lip or palate, achondroplasia, or Down syndrome, and, similarly, speech recognition AI tools also struggle to process the words of people with deaf affect, speech impairments, and so on (Tilmes, 2022).

Conclusion

The word 'desirable' hints at how the efforts to build new futures are founded on positive visions of social progress (Jasanoff and Kim, 2015), but as Preece, Whittaker and Janes (2022) recognise, studying sociotechnical imaginaries is also about undesirable futures. In this paper, we have analysed interviews with 12 companies in Italy that either design (vendors) or use (clients) AI-rec-tech to explore how they perceive these systems in relation to social inequality. We have highlighted three sociotechnical imaginaries: the third eye, the river, and the car bonnet. Through critically analysing these imaginaries, we have shown that prioritisation of talent capture and productivity means that these systems are unlikely to promote social equality in the Italian context. While this is not surprising, given the Italian government's prioritisation of innovation and productivity over the social impact of technology (Saracco, 2022; Foffano, Scantamburlo and Cortés, 2023), this paper provides evidence and nuance to what is behind these views and how they relate to the design and use of AI-rec-tech, and discusses the potential implications of these visions. It demonstrates that the sociotechnical imaginaries that vendors and clients share for AI-rec-tech are leading us towards an 'undesirable' future of hiring that continues to perpetuate social inequality. Moreover, it is worth vendors and clients alike realising that taking more interest to integrate imaginaries of social equality into their design and use would benefit their business interest, as there has long been seen to be a connection between diversity and business performance (Eswaran, 2019; Hakovirta *et al.*, 2020).

This paper contributes to a small emerging body of research within sociology and communications that presents empirical data on AI-rec-tech to discuss the potential impacts of AI-rec-tech systems. It also contributes to broader literature within critical data studies and science and technology studies surrounding the potential societal implications of AI regarding inequality and discrimination. This study lays the groundwork for further research on these topics that should aim to investigate how these systems are impacting people in practice and whether they promote demographic diversity and equality in hiring. This would get to the heart of how these sociotechnical imaginaries are enacted and the real-life impact they have (Joyce *et al.*, 2021). Moreover, it lays the foundation for broader future work concerning inequalities in hiring and the labour market. If these systems do perpetuate social inequalities, we should ask how this might influence the values and mission of certain sectors and industries, and how this might have broader consequences for our society politically, economically, and socially.

AI use disclosure

No generative AI tools were used in the research or writing of this article. As discussed in our Methods section, Microsoft Teams transcription service, which uses AI, was used to transcribe interviews. In addition, DeepL, an AI-powered translation tool, was used to translate interview transcriptions from Italian to English.

Author contributions

Both authors contributed equally to this work.

Data and code availability

The data underlying this article cannot be shared publicly owing to the anonymity and trade secrets of certain companies and individuals. The data will be shared on reasonable request to the corresponding author.

Declaration of interest statement

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical approval

This research has been considered on behalf of the Social Sciences and Humanities Interdivisional Research Ethics Committee (IDREC) at the University of Oxford and is in accordance with the procedures laid down by the university for ethical approval of all research involving human participants. The reference number is OII_C1A_23_005.

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