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Transparency in the datafied workplace: Law, workers, and job applicant perspectives

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ABSTRACT

As AI systems become increasingly embedded in the workplace, and the datafication of recruitment and employment grows more pervasive, ensuring the trustworthiness of these technologies from design to deployment has emerged as a pressing concern - particularly within the European Union's evolving regulatory framework. The General Data Protection Regulation (GDPR) and the AI Act play a key role in shaping the governance of AI, including in recruitment and employment. Drawing on a large-scale survey conducted as part of the BIAS project, our study analyses 4317 valid responses from a diverse sample across the European Union, Iceland, Norway, Switzerland, and Turkey. It examines how job applicants and workers perceive and experience AI systems, their awareness of AI use, and their experiences with data processing and transparency mechanisms, paying particular attention to demographic patterns related to gender, age, and education. Our findings reveal that transparency measures, while sometimes present, remain fragmented and procedural. Opt-out mechanisms are also frequently unclear. AI systems in recruitment contexts collect substantially more data, particularly on sensitive topics. In workplace settings, data collection is lower and differences between sensitive and non-sensitive information are less pronounced. Subjective minority identification appears to be the most consistent demographic predictor of higher likelihood of data collection. Building on these findings, the article critically assesses how transparency is, and should be, operationalized under the GDPR and the AI Act. It argues for aligning legal compliance with practices that centre the experiences of those most affected and address structural inequalities in recruitment and employment.

1. Introduction

Since the 1990s, the adoption of digital technologies has progressively transformed human resource (HR) practices, including recruitment and selection, workforce planning, and performance evaluation (Aguinis et al., 2024; Bartram, 2000; Bujold et al., 2023; Kellogg et al., 2020; Köchling & Wehner, 2020; Strohmeier & Piazza, 2015). These advancements are often praised for their potential to enhance efficiency, reduce costs, and enable greater flexibility (Gonzalez et al., 2022; Jarrahi, 2018; Koivunen et al., 2019; Langer et al., 2021; Sánchez-Monedero et al., 2020; Sharone, 2017; Sousa & Wilks, 2018). Over time, these digital infrastructures have laid the groundwork for the more recent integration of artificial intelligence (AI) into the workplace, extending and amplifying earlier trends in digital HR management (Rigotti & Fosch-Villaronga, 2024). Not uncritically, proponents often portray these systems that combine human judgment with data-driven insights as tools that support more objective decision-making (Cowgill, 2019; Dencik & Stevens, 2023; P. T. Kim, 2016; Larsson et al., 2024; van Esch et al., 2019). However, the perceived benefits of earlier digital tools and current AI systems are accompanied by significant risks, particularly for job applicants and workers already in structurally vulnerable positions marked by power imbalances (Kingsley et al., 2015). Research consistently shows that the design and deployment of these technologies are far from neutral or inclusive (Dastin, 2018; E. J. Kim et al., 2020; Veldanda et al., 2023; Yarger et al., 2019). Instead, they often reproduce and reinforce structural inequalities within society, particularly through the ways in which personal and non-personal data is processed and used to inform HR decisions (Carter,

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2025).

AI systems rely on processing personal and sensitive data, like gender, professional experience, and age, both during the design phase, via training datasets that often reflect biased and unrepresentative workforce profiles, and during deployment, through the continuous collection or inference of information about job applicants and employees (Bernhardt et al., 2023; Sánchez-Monedero et al., 2020; Todolí-Signes, 2019; Warter, 2025). However, transparency regarding how such data is used, stored, or shared is often limited or superficial (Calacci & Stein, 2023). Crucially, the opacity that characterizes the design and deployment of AI systems - frequently defined by imperceptible and faceless mechanisms - can erode trust among workers, diminish understanding of decision-making processes, weaken accountability, and suppress collective resistance within the workplace and in legal fora (Aloisi, 2024; Hunkenschroer & Kriebitz, 2023; Sánchez-Monedero et al., 2020). Taken together, these dynamics can negatively impact the dignity, agency, and overall well-being of job applicants and workers, shaping not only their immediate working conditions but also their longer-term access to economic resources, social belonging, and health (Rigotti & Fosch-Villaronga, 2024; Todolí-Signes, 2019; Yam & Skorburg, 2021). On a broader scale, these dynamics also undermine the socio-technical foundations of a just and democratic society, raising pressing questions about accountability and governance in the use of AI at work (Yeung, 2019).

Over the past decade, Regulation (EU) 2016/679 - better known as the General Data Protection Regulation (GDPR) - has governed data processing across the European Union, including workplace settings. This legislation aims to balance the legitimate interests of employers with the reasonable privacy expectations of job applicants and workers (Article 29 Data Protection Working Party, 2017). This balancing of interests and protection of rights must now be understood in conjunction with Regulation (EU) 2024/1689 (hereinafter AI Act or AIA), which establishes harmonized rules for AI systems developed, marketed, or used within the EU internal market. The AI Act explicitly designates AI systems used in employment, worker management, and access to self-employment as 'high-risk' under Annex III(4), while potentially extending to the informal use of AI systems in the workplace (Rigotti et al., 2026; Özkiziltan & Landini, 2025). Additionally, it introduces a series of obligations concerning transparency, applicable to both AI developers and employers. In this evolving landscape, it is crucial to examine how the interplay between the GDPR and the AIA can be used to safeguard transparency, data protection, and other fundamental rights of job applicants and workers in an increasingly datafied workspace. This is particularly pressing in light of growing criticism that the GDPR, despite its foundational role, offers limited tools for addressing the distinct risks posed by automated decision-making in employment (Aloisi, 2024; Hacker, 2018; Parviainen, 2022; Zuiderveen Borgesius, 2020), and the yet underexplored potential of the AI Act to fill these regulatory gaps.

Accordingly, this article examines how transparency is and should be interpreted and operationalized in the context of AI systems in the labor market. Our starting point is a tension that sits at the intersection of regulatory ambition and empirical reality. Transparency, primarily operationalized through disclosure, is increasingly positioned as the central mechanism for protecting job applicants and workers from AI-driven risks. Yet, the conditions under which such transparency is expected to function are precisely the conditions under which disclosure-based approaches are known to be least effective: structural power asymmetry, bounded rationality, and differential exposure to harm amongst socially marginalized groups. The populations that transparency is most urgently designed to protect may be structurally least able to benefit from it as currently conceived, a tension that has not been examined empirically. Most recent scholarship has approached the issue from a normative, technical, or institutional perspective, rather than from the standpoint of those who directly experience these technologies in practice (Ajunwa, 2020; Al Sulait et al., 2024; Felzmann, 2019; Krook et al., 2025). Grounding governance in their lived realities could help prevent legal and policy responses from remaining abstract or technocratic, and promote meaningful, legitimate oversight. As a first empirical step in this direction, we draw on quantitative data from a large-scale survey conducted as part of the [omitted for review] project. Based on 3294 responses from a diverse sample across the European Union, Iceland, Norway, Switzerland, and Turkey, the survey provides novel insights into how workers and job applicants perceive and experience AI in the workplace.

Specifically, the analysis focuses on two dimensions that follow directly from this theoretical tension. First, we examine the degree of transparency in the interaction between users and AI systems, understood as the extent to which job applicants and workers are aware of such interactions, operationalizing the question of whether disclosure-based transparency is actually reaching those it is meant to protect. We find that transparency measures, while sometimes present, remain fragmented and procedural, and opt-out mechanisms are frequently unclear. These limitations reduce genuine user agency over data control, and stress that transparency must ensure information is understandable, accessible, and actionable. Second, we examine the sensitivity of the information requested, measured by the topics raised by the AI system during the interaction, operationalizing the question of whether exposure to potentially harmful data collection is distributed unequally across demographic groups. Here, we find that AI systems in recruitment contexts collect data on substantially more topics, particularly sensitive ones, whereas employment settings involve collection on fewer topics overall and less distinction between sensitive and non-sensitive issues. Subjective minority identification is the most consistent demographic predictor of higher likelihood of data collection. By examining these two dimensions, we assess whether particular individual characteristics could be associated with (1) reduced awareness of AI-driven interactions, and (2) increased exposure to sensitive questioning.

Overall, our study serves as a foundation for evidence-based policy recommendations aimed at enhancing AI transparency in the workplace. However, it is important to be explicit about what this study can and cannot contribute. It provides novel empirical evidence on whether the theoretical gaps identified above manifest in workers' and job applicants' reported experiences. It cannot, however, establish the causal mechanisms underlying these patterns. In particular, it definitively distinguish between different significance, different recall, and different system behavior, though the latter is addressed. It can, however, provide the empirical grounding necessary for regulatory and design responses that are socially informed rather than purely technocratic.

The paper is structured as follows: Section 2 examines the concept of transparency in the workplace, addressing its conceptual complexity, its relationship to GDPR and AIA compliance, and the importance of adopting a bottom-up approach to research. Section 3 outlines the methodological approach, including data collection procedures and analytical methods. It draws on a survey conducted as part of the [omitted for review purposes] project, which assesses respondents' awareness of AI use in the workplace and recruitment settings, as well as the types of information collected by AI. In Section 4, we analyze the results obtained through the survey. An empirical strategy has been developed to uncover hidden patterns in the use of AI systems in the workplace, considering various demographic characteristics. Section 5 discusses the broader implications of these findings and reflects on the study's limitations. Finally, the conclusion considers how these insights may inform the future operationalization of the GDPR and AIA in research and policymaking.

2. Research background

2.1. Transparency in the datafied workplace

One of the most significant developments in the workplace is its growing datafication (Carter, 2025; Mettler, 2024; Sánchez-Monedero &

Dencik, 2019), whether driven by administrative optimization or the extraction of informational capital (Simitis, 1999). From the outset of the hiring process, job applicants are routinely required to disclose personal information, including professional experience, educational background, or personality traits, often through application forms and interviews. Increasingly, however, personal data are not just disclosed but inferred or predicted through AI, as job advertising and recommender systems selectively target certain demographics (Dalenberg, 2018; Sánchez-Monedero & Dencik, 2019). Once employed, data collection becomes even more pervasive. Communications tools such as phones and computers are frequently monitored and, in some contexts - like platform-based service delivery - function as the primary interface between employer and worker (Ball, 2021; Hickok & Maslej, 2023; Jarrahi et al., 2021; Sebastian et al., 2025). Similarly, new data sources like social networks, shared calendars, and collaborative platforms (*e.g.*, Slack, Microsoft Teams) are integrated to extract insights into work tasks and individual behaviors, social interactions, and even future actions (Sánchez-Monedero & Dencik, 2019). Simultaneously, AI systems for performance management rely on productivity metrics, communication patterns, or behavioral proxies like response times, task completion rates, or customer ratings, to evaluate workers, often without clear disclosure of how these indicators are weighted or interpreted (Jarrahi et al., 2021). For instance, delivery drivers are monitored through GPS tracking and in-vehicle cameras, which employers claim helps assess speed, route efficiency, and signs of fatigue or stress (Sebastian et al., 2025). Wearable devices are also increasingly embedded across the employment lifecycle, sometimes under the guise of occupational health and safety (Ball, 2021). This ongoing datafication raises profound questions about how much workers and job applicants know about the systems shaping their opportunities and conditions, making transparency a crucial, yet underexplored, issue.

In the literature, several risks and harms have been identified in connection with the pervasive processing of personal data in the workplace. A key concern is the distortion of employers' and HR practitioners' perceptions, which can fuel biased assessments and reinforce exclusionary dynamics (Hendrickxt, 2019; Otto, 2015; Simitis, 1999), thereby reproducing a demographically and culturally monolithic workforce (Bodie et al., 2017). Such biased outcomes can arise unintentionally and without the awareness of those making employment decisions. For example, LinkedIn's job-matching algorithm reportedly downgraded applicants living outside the country of the job listing, regardless of their qualifications, without informing either recruiters or candidates (Kayser-Bril, 2021). Simultaneously, job applicants and workers face an erosion of personal autonomy, as they lose control over how they present themselves and how their data are collected and processed (Bodie, 2022; Sharone, 2017). Even non-sensitive data can become sensitive once processed through inference, profiling, or aggregation (Carter, 2025), shaping key aspects of working life like the way and pace of work, task allocation, scheduling, career progression and evaluation criteria (Brey, 1999; Unruh et al., 2022). These concerns are exacerbated by a growing overreliance on AI systems, which may displace human judgment and obscure the reasoning behind key decisions (Leicht-Deobald et al., 2019), raising difficult questions of accountability. In contexts where AI is deployed not only to assist but also to amplify or replace HR practices, like monitoring performance, managing workflows, or making complex assessments, it becomes increasingly difficult to establish clear lines of responsibility between human and technological actors (Bankins et al., 2022).

Many scholars trace the risks associated with the constant data processing of AI systems in recruitment and employment to pre-existing, technical, and emergent biases (Fabris et al., 2025; Friedman & Nissenbaum, 1996). Pre-existing biases reflect patterns in historical data and societal inequalities encoded into these systems. For instance, Amazon abandoned an AI recruiting tool after it systematically downgraded resumes associated with women, having been trained on a decade of predominantly male hiring data (Dastin, 2018). Similarly, several generative AI models used for online job postings have been found to favor men, particularly for higher-wage roles (Chaturvedi et al., 2025). Technical biases arise from limitations or design choices in development. For example, AI-powered interviewing tools have produced higher error rates in speech recognition for non-native English speakers or individuals with speech-affecting disabilities, due to training datasets that overrepresent American English and underrepresent other linguistic or accessibility contexts (Sheard, 2025). Emergent biases develop after deployment, as AI systems interact with new societal contexts or norms. Job ad delivery systems for STEM careers, for example, have been shown to disproportionately reach men, even when ad content is gender-neutral (Lambrecht & Tucker, 2019). All these forms of bias are deeply entangled with broader structures of privilege and exclusion (Krook et al., 2025; Rigotti & Fosch-Villaronga, 2024). In this paper, however, the primary focus lies on a distinct and compounding challenge: the opacity of these technologies, which obscures how such biases operate and limits individuals' ability to perceive or contest their effects.

Often referred to as the 'black box' problem (Ajunwa, 2020), this opacity stems from the complexity of AI systems and the lack of visibility into how they process data, draw inferences, or produce outcomes. Because decision-making criteria and underlying assumptions remain hidden, those affected by AI systems are frequently unable to understand, contest, or influence decisions that impact them. Unsurprisingly, this lack of transparency is already recognized by job applicants and workers as a source of unfair treatment (Armstrong et al., 2023). It permeates the entire employment lifecycle - not only in how personal and non-personal data is collected, processed, and shared, but also in the concealed assumptions, underlying logics, and design objectives that influence decision-making processes within the HR ecosystem. Importantly, this opacity exacerbates existing information asymmetries within the inherently unequal employer-worker relationship, as well as job applicants (Gaudio, 2022). However, AI systems often remain inscrutable even to those who implement them, like employers and HR practitioners, making it difficult for decision-makers to interpret, justify, or contest outcomes for which they remain formally accountable (Gaudio, 2022). These dynamics highlight that the challenges posed by AI in the workplace go beyond questions of efficiency and accuracy, underscoring how the visibility of technological processes to end-users and affected groups plays a key role in shaping what workers and job applicants know about - and how they interpret - AI-driven decision-making.

It is precisely this gap between the growing influence and the opacity of AI systems that has led transparency to emerge as a potential counterbalance (Hacker & Passoth, 2022; Krook et al., 2025). Transparency is increasingly framed not merely as a procedural safeguard but also as a normative principle aimed at levelling the informational playing field between employers and HR practitioners on the one hand, and workers and job applicants on the other (Al-Sulaiti et al., 2024; Bankins et al., 2022; Zieglmeier & Pretschner, 2023). By rendering AI systems more intelligible, transparency can expose underlying assumptions, decision-making logics, and data sources shaping AI outputs. This visibility is essential in addressing both prospective concerns, informing in advance workers and job applicants about how their data will be used and by whom, and retrospective concerns, enabling them to trace and challenge decisions that impact them (Felzmann, Villaronga, et al., 2019). Practically, this entails ensuring that communications around data processing are easily accessible, clearly formulated, and presented in plain language. This is particularly important when explaining data provenance and the intended purpose of the AI system (Müller & Lazar, 2024). It also requires embedding explainability and traceability at the decision and system levels, so that outputs can be meaningfully interpreted and verified by different stakeholders (Al-Sulaiti et al., 2024; Larsson & Heintz, 2020; Müller & Lazar, 2024). In that sense, because transparency serves different functions for different actors, it cannot be conceived as a uniform obligation. Different stakeholders involved in the design and deployment of AI systems in the workplace, including AI

developers, HR practitioners, and workers, should be subject to differentiated transparency expectations and obligations, reflecting their respective roles and capacities to act on the information provided (Weller, 2019).

Yet, transparency is complex and context-dependent (Larsson & Heintz, 2020; Weller, 2019). In practice, it is frequently reduced to a narrow, one-off disclosure of information that falls short of a more substantive, multidimensional accountability. While the provision of information is undoubtedly important, its value is shaped by the relational and organizational context in which it is delivered (Felzmann, Fosch-Villaronga et al., 2019; Stohl et al., 2016), its intended purpose and the audience it targets (Hacker & Passoth, 2022). The limitation of disclosure-based approaches is well documented in the literature on informed consent to data processing, and this literature does more than add context: it provides a direct theoretical critique of the assumption that transparency can be achieved primarily through disclosure. Although disclosure is meant to enable careful deliberation and risk assessment, in practice individuals' decisions are constrained by bounded rationality, incomplete information, time pressure, and cognitive biases (Custers et al., 2022; Marsoof & Gupta, 2025; Utz et al., 2019). Importantly, these constraints are most severe for individuals considered vulnerable data subjects (Malgieri & Niklas, 2020), those in structurally disadvantaged positions, including workers and job applicants whose bargaining power is inherently limited by the employment relationship (Article 29 Data Protection Working Party, 2018a, 2018b). Because disclosure-based transparency depends on recipients being able to deliberate on and act upon the information provided, its protective function is weakest precisely where the need for protection is greatest. Moreover, the collective dimensions of AI decision-making compound this problem further: outcomes are determined not only by an individual's own data but also by patterns and correlations derived from the data of others (Abraha, 2022), and efforts to explain a system's internal logic may risk disclosing proprietary information to unintended audiences (Krook et al., 2025). These dynamics challenge prevailing data protection assumptions, including the idea that limiting or prohibiting the collection of sensitive personal data inherently reduces the risk of discrimination (Williams et al., 2018), and highlight the need for transparency mechanisms that are substantive, context-aware, and resistant to "transparency-washing."

This critique gains further force when read alongside the literature on AI bias introduced above, whose implications for transparency remain underexplored. Research shows that AI systems in the workplace reproduce and amplify social inequalities (Köchling & Wehner, 2020; Rigotti & Fosch-Villaronga, 2024). If the harms of AI systems fall disproportionately on socially marginalized groups, and if disclosure-based transparency is least effective for those same groups, the assumption that transparency can serve as an effective safeguard is doubly undermined. Disclosures may fail to reach those who need them most, while those most exposed to harm may also be least positioned to act on the information provided. The "black box" nature of AI systems further amplifies this problem (Ajunwa, 2020; Andrada et al., 2023; Busuioc, 2021): where decision-making criteria remain hidden, those affected cannot understand, contest, or seek redress for outcomes that impact them. In high-stakes workplace settings, such as performance ratings that trigger termination or block promotion, the consequences of this opacity may be irreversible (Ertemel et al., 2021).

Against this background, achieving meaningful transparency requires more than simply meeting legal obligations. It involves balancing multiple demands: recognizing the structural power asymmetries inherent in employment relationships, providing accessible and actionable information, and fostering a technological and organizational culture grounded in accountability and continuous dialogue. These efforts must align with existing legal frameworks, most notably the GDPR and the AI Act, both of which set out important but incomplete transparency obligations for AI design and use in employment settings. Given the conceptual and practical challenges associated with transparency, as well as its far-reaching implications for data processing and the design and deployment of AI systems in the labor market, the following subsection explores how these two legal instruments address transparency-related obligations in recruitment and employment.

2.2. Transparency at work under the GDPR and the AIA

The GDPR establishes transparency as a foundational principle for the protection of personal data. Enshrined in Article 5.1(a) and elaborated in Recital 39, transparency is closely linked to the principles of fairness and accountability, with the overarching aim of fostering trust in data processing activities (A29WP, 2018; De Terwangne, 2020). As clarified by the Article 29 Data Protection Working Party (2018b), transparency empowers individuals by enabling them to understand and, where necessary, contest any data processing that affects them. Recital 39 underlines that it should be clear to data subjects when and how their personal data are being collected, used, or otherwise processed, and to what extent such processing occurs. Although this language does not correspond to a single, clearly defined obligation, it signals a substantive expectation of clarity and openness (De Terwangne, 2020). The recital further emphasizes that information provided to data subjects must be easily accessible, comprehensible, and conveyed in plain language. These principles are operationalized through Articles 12 to 14 GDPR, which set out concrete obligations for controllers to provide timely and comprehensible information about data processing. Specifically, Article 12 GDPR establishes the procedural conditions under which information must be provided, thereby enabling the effective exercise of data subject rights (Polčák, 2020). While it does not create substantive rights, Article 12 ensures that these rights are practically realizable by requiring proportionate, clear, and timely communication from controllers to individuals. Articles 13 and 14 GDPR, in turn, require that data subjects are informed by the controller about the details of the processing activity, including the purposes and legal basis and the data subjects' rights at the time when the controller collects personal data directly from them or at the time of first communication with the subject or third-party disclosure, whichever comes first (Zanfir-Fortuna, 2020a, 2020b).

These articles are highly relevant to AI in recruitment and employment. As early as 2017, the Article 29 Working Party acknowledged the growing data protection risks of increasing workplace datafication, stressing that workers must receive clear, and accessible communication regarding any monitoring activities, including their purposes, scope, and context, as well as the available means for workers to prevent or limit the capture of their data through such technologies (A29WP, 2017). This emphasis on transparency reflects a broader feature of data protection in the workplace: consent is generally not regarded as a reliable or legitimate basis for processing, given the structural imbalance of power between employer and employee (A29WP, 2017). In this setting, transparency becomes a primary means through which job applicants and workers can obtain information about, and exercise some degree of control over, the processing of their personal data. Other GDPR provisions, like the right to object to profiling (Article 21), the prohibition of solely automated decision-making (Article 22), and the obligation to conduct data protection impact assessments, reinforce the principle of transparency in employment contexts (Aloisi, 2024; Gaudio, 2022; Hacker & Passoth, 2022; Hendrickxt, 2019). Article 88 GDPR also allows Member States and social partners to adopt more specific rules for data protection in the employment context through legislation or collective bargaining agreements. For example, Spain requires consultation with trade unions before the installation of monitoring technologies in the workplace (Gaudio, 2022). However, much of the scholarship questions whether the GDPR alone is sufficient to adequately address the scale and complexity of data processing practices and transparency challenges (Dewitte & Ausloos, 2024; Wulf & Seizov, 2024), particularly within the context of the labor market (Rigotti & Fosch-Villaronga, 2024). Simultaneously, some scholars have argued that data protection law should

not be considered or applied in isolation, but rather in conjunction with other relevant legal instruments (Aloisi, 2024; Rigotti et al., 2026), most notably the AIA.

The AIA explicitly complements existing Union law (Recital 9). Unlike the GDPR, however, the AIA regulates the design and use of AI systems in the workplace. In particular, Article 5.1(f) AIA prohibits the placing on the market, deployment, or use of AI systems intended to infer individuals' emotional states in the workplace, with its Recital 44 citing serious concerns about their scientific validity, limited reliability, lack of specificity, and restricted generalizability. Additionally, Recital 57 AIA acknowledges that AI systems in the workplace can profoundly impact career trajectories, livelihoods, and workers' rights, potentially perpetuating historical patterns of social discrimination and infringing upon fundamental rights like privacy and data protection. In response, the AIA classifies AI systems used in HR practices as 'high-risk.' Annex III, Section 4(a) designates as high-risk AI systems intended for use in recruitment and selection processes, like targeted job advertising, application screening, and candidate evaluation, pursuant to Article 6 (2). In parallel, Annex III, Section 4(b) extends this classification to AI systems used in employment-related decisions, including promotions, dismissals, task allocation based on personal characteristics, and the monitoring or assessment of workers' performance and behavior.

As a result of the risk classification, the AIA imposes stringent obligations in its Chapter III, which apply to AI developers or employers deploying third-party applications to manage workers, job applicants, or self-employed individuals in the EU (Article 2). Several of these obligations are directly linked to transparency, though they have been critiqued for their technocratic and managerial approach to AI governance (Svitych, 2025) and for offering limited protection to affected groups' rights (Hacker & Passoth, 2022; Özkiziltan & Landini, 2025). Article 13 AIA, for example, requires that high-risk systems must be accompanied by clear, comprehensible, and actionable information for users like employers or HR professionals. This includes details on the system's purpose, limitations, risks, and operational guidance, positioning transparency as a functional design feature, not merely a disclosure obligation. However, scholars have questioned the provision's practical enforceability (Busuioc et al., 2023; Svitych, 2025). Transparency is also linked to other requirements (Hacker & Passoth, 2022), including Article 10 AIA on data governance. This provision mandates that training and testing data be high-quality, representative, and well-documented, including efforts to address bias, subject to safeguards when processing sensitive data. Importantly, Article 10 AIA must be read in conjunction with the GDPR. Article 26(9) AIA reinforces this link by requiring that AI Act documentation support GDPR compliance, including data protection impact assessments. Nonetheless, these provisions raise questions about who transparency is actually designed for and whether the informational needs of its recipients, in this case, workers, are adequately taken into account within increasingly complex regulatory and documentation obligations.

This question becomes particularly significant when examining how the AIA differentiates between AI systems and allocates transparency obligations accordingly. Not all AI systems used in the workplace automatically fall under the high-risk category (Rigotti et al., 2026; Özkiziltan & Landini, 2025). For instance, employers may utilize general-purpose AI (GPAI) models for tasks like drafting emails and generating job advertisements. Under Article 53 AIA, GPAI providers are required to maintain detailed documentation of development and testing processes, thereby ensuring a baseline level of transparency by making such information available to downstream deployers, with exceptions for open-source or publicly accessible tools. Conversely, AI systems with direct implications for employment decisions, such as recruitment chatbots, emotion recognition systems, or biometric categorization systems, are subject to stricter transparency obligations under Article 50 AIA. Employers using these systems must inform job applicants and workers about the use of such technologies, ensuring that their deployment aligns with the AIA's transparency principles and does not compromise fundamental rights. However, scholars have raised concerns about the effectiveness of this information requirements, arguing that they may turn technically unfeasible (Krook et al., 2025). Moreover, certain AI systems in workplace settings, like meeting schedulers or multi-purpose tools, fall into a residual low-risk category not explicitly regulated by the AIA. While their unrestricted use may promote innovation and ease of adoption, it raises concerns about potential regulatory circumvention. The absence of explicit oversight may allow these tools to bypass stricter transparency requirements, limiting workers' ability to fully understand or contest decisions that affect their employment and professional development. Nonetheless, where such systems process personal data, the GDPR continues to apply, ensuring a minimum level of transparency.

On a final note, it is important to recall that, from an ethical perspective, transparency is a cornerstone of the AIA's risk-based approach to fostering trustworthy AI. Rooted in the *Ethics Guidelines for Trustworthy AI* by the High-Level Expert Group on AI HLEG (2019), Recital 27 AIA frames transparency as requiring that AI systems be designed and used in ways that enable appropriate levels of traceability and explainability. This includes ensuring that individuals are aware when they are interacting with an AI system, that deployers are informed of the system's capabilities and limitations, and that affected persons can understand their rights in relation to the system's use.

2.3. Beyond legal compliance: understanding AI transparency through workers' and job applicants' perspectives

While much research has examined transparency through the lens of the GDPR and its stakeholders (Bowyer et al., 2022; Buckley et al., 2024a; Mangini et al., 2020), occasionally focusing on workplace contexts (Buckley et al., 2024b), far less is known about how AI transparency is understood and experienced by workers and job applicants themselves, a gap identified as particularly pressing in the literature (Armstrong et al., 2023). Capturing these perspectives is essential, and the theoretical tensions identified in the previous sections make clear why. Both the literature and the legal frameworks examined above assume that transparency can serve as an effective counterbalance to the power asymmetries and opacity of AI-driven decision-making. Yet as the same literature suggests, this assumption is most likely to fail for the groups it is most meant to protect: those in structurally disadvantaged positions might simultaneously be the most exposed to harm and the least able to act on whatever information is provided. Grounding governance in their lived realities is therefore not only desirable but necessary to prevent legal and policy responses from remaining abstract or technocratic, and to promote meaningful, legitimate oversight.

Existing quantitative research on AI use in the workplace reinforces this concern, and in particular highlights the gap between AI's growing pervasiveness and workers' actual awareness of it. The European Center for the Development of Vocational Training (CEDEFOP) survey of 5342 employees across eleven Member States in 2023 found that around one in seven adult workers regularly use digital tools or applications that automate specific tasks through algorithms, with 22% of workers frequently employing tools for text recognition, translation, transcription, and generation, and 28% that report (either they or their colleagues) relying on AI systems as a core aspect of their job functions (CEDEFOP, 2024). Similarly, the European Central Bank's 2024 Consumer Expectations Survey found that about one-quarter of workers surveyed in eleven Member States, predominantly males aged 18 to 34, acknowledged using AI tools at work (Dias da Silva and Weißler, 2025). However, greater exposure to technology does not necessarily lead to greater awareness or understanding, particularly in a digital environment saturated with information, distractions, and repetitive consent requests that can lead to 'transparency fatigue' (Choi et al., 2018) and, ultimately, reduced engagement with individual rights.

This gap between formal transparency and substantive understanding is further illustrated by evidence on how organizations and workers

relate to transparency in practice. Despite considerable emphasis on GDPR compliance in the marketing of AI systems for HR practices (Rigotti et al., 2025), and with data subjects appearing increasingly aware of their rights (European Commission, 2024), it is uncertain whether workers and job applicants interacting with AI (Bunwaree et al., 2025) fully understand when and how their data are collected and processed. Conversely, companies often deprioritize transparency as a practical objective - with legal compliance ranking among the least relevant motivations for its operationalization (Molavi Vasse'i & McCrosky, 2023), even though research shows that transparency practices foster more positive attitudes toward AI systems among workers and job applicants (Bujold et al., 2023; Horodyski, 2023; Hu et al., 2024; Park et al., 2021; Wiener et al., 2023; Yu et al., 2023). This mismatch is compounded by widespread low levels of AI literacy and familiarity (CEDEFOP, 2024), which is often attributed to insufficient transparency in the design and implementation of these systems and that undermines workers' and job applicants' ability to understand, trust, or challenge how their data is used.

3. Methodology

To empirically examine how AI systems use in recruitment and employment are perceived and experienced by job applicants and workers, this study focuses on two analytical dimensions: (1) the level of transparency in user-AI interactions, defined as how aware a job applicant or worker is of engaging with an AI system, and (2) the sensitivity of the information involved, measured by the nature of topics introduced by the AI during the interaction. The goal is to determine whether certain individual characteristics are associated with (1) reduced awareness of these interactions, and (2) a higher likelihood of being exposed to sensitive topics, both in recruitment and employment contexts.

3.1. Data

We use survey data collected as part of [omitted for reviewing purposes] project. This survey consisted of four modules, totaling 36 questions. The first module investigates whether respondents have had prior experience with AI systems in recruitment and employment, establishing a baseline for their familiarity with these technologies. The survey did not provide a formal definition of AI or explicitly test respondents' technical understanding of the term, a deliberate choice to avoid privileging expert framings over the everyday interpretations of those whose perceptions and experiences the study seeks to capture. To anchor respondents' interpretations in recognizable examples, the module included references to widely used platforms and applications. Specifically, respondents were asked: **Q1.1** *Do you know that LinkedIn and other social media platforms for professional networking and career development use AI?* and **Q1.2** *Do you know that employers increasingly use AI applications to identify candidates, screen job applications, conduct interviews, train employees, improve teamwork, and inform decisions about promotion or dismissal?* The second module focuses on respondents who have interacted with AI systems, including insights into their experiences with data protection and transparency. The third module explores broader attitudes, mapping respondents' perspectives on the role and implications of AI systems in the labor market. Finally, the fourth module captures demographic characteristics and diversity-related information about respondents. To enhance accessibility, the survey was translated into 27 European languages. Translations were carried out by native speakers who, while not professional translators, were internal and external Consortium members familiar with the relevant cultural and organizational contexts. The survey received clearance from the Norwegian Data Protection Authority.

Data were collected through Qualtrics in November 2023,[1] yielding 4920 responses, of which 4901 consented to participate and 19 declined. Respondents were compensated at an average rate of £7.50 per hour, with a mean completion time of approximately 8 min.

We applied a five-step cleaning process to ensure data quality and validity. First, all incomplete questionnaires were discarded. Second, duplicate entries were removed by identifying identical participant IDs on Prolific. Third, responses from individuals residing outside the European Union, Iceland, Norway, Switzerland, or Türkiye were excluded because they fell outside the geographical scope of the study. Fourth, responses flagged with a Qualtrics Fraud Score above 30, which indicates a high likelihood of duplicate or fraudulent entries, were eliminated. Finally, responses from participants who indicated that they did not wish to participate were removed. To avoid any concerns about validity arising from combining both samples, we have decided to present our main results using only the data from the second survey, which yielded a total of 4024 observations after cleaning. However, the results for a pooled sample with fixed effects over time are presented in the appendix as a robustness check.

Table 1 summarizes the sample composition. The sample was deliberately designed to oversample younger and highly educated co-

Table 1
Sample statistics

Group	Respondents	Percentage
Total	4024	100 %
Gender		
Male	1996	50.1 %
Female (and other)	2006	49.9 %
Age		
Younger than 40 years-old	3439	85.6 %
40 years-old or older	577	14.4 %
Education		
Less than bachelor's degree	1112	28.5 %
Bachelor's degree or higher	2787	71.5 %
Type of AI interaction		
Recruiting only	1008	28.25 %
Workplace only[a]	2560	71.75 %

[a] Training, improving performance, promoting, sanctioning misconduct and foreseeing conducts.

[1] A first wave of data was collected approximately six months prior to the Prolific survey through a university research consortium, yielding 293 useable observations after applying the same eligibility and data quality criteria. The Prolific data were analyzed before this second wave was collected; the consortium survey was identical in design and was not used as a pre-test to refine the instrument. We do not include the consortium data in the main analysis because pooling two non-probability samples collected six months apart raises comparability concerns: the consortium sample is older, more female (57% vs. 50%), and considerably more highly educated (93% with tertiary education vs. 71%) than the Prolific sample, and at 293 observations it is too small to support reliable regression estimates independently. In the interest of transparency, descriptive characteristics of the consortium sample and a full side-by-side comparability table are reported in Appendix A.

horts while keeping a gender-balanced panel, as these groups are more likely to use online platforms for job search and work in roles where AI systems are common - as seen in comparable studies (Dias da Silva & Weiβler, 2025). Although older and less formally educated were under-sampled because they are less exposed to these contexts, this focus allowed us to gather more relevant data for our research questions.

3.2. Empirical strategy

Our empirical strategy consists of two parts. The first provides a descriptive overview of transparency practices, focusing on whether respondents were informed about the use of AI systems during recruiting and in the workplace. The second examines the content of information requested by AI systems, using regression analysis to assess whether specific individual characteristics are associated with being asked about sensitive or non-sensitive information.

For the first part of the analysis, we relied on four questions related to transparency: (1) **Q 7**. *When interacting with AI applications, have you been informed about its use?* (yes or no), (2) **Q 7.1** *[…] when were you informed about?* (before or after the interaction), (3) **Q 7.2** *[…] what were you informed about?* (How your personal data were expected to be used, how the AI works, why the AI was used, etc.), and (4) **Q 7.3** *[…] how was the information presented to you?* (orally or written). We also considered whether respondents were given the possibility of opting out during the interaction with the AI system, based on **Q 8** of the survey: *Could you opt out of the use of AI applications?* Table 2 shows the distribution of responses for each of these questions:

For the second part of the analysis, we relied on a survey question about the *content* of the information requested during AI interactions: *When interacting with AI applications, have you ever been directly asked about your … ?* This question included 20 items covering a wide range of personal details, as shown in Table 3. Respondents could select multiple answers. The most requested information includes age (67.2%), gender (47.34%), education (44.51%), spoken language (41.35%), and previous work experience (38.54%). In contrast, the collection of information regarding genetics (1.12%), trade union membership (1.39%), and political affiliation (2.24%) is significantly less common *(see* Table 3*)*.

Table 2
Questions related to transparency.

Question	Respondents	Percentage
Total	4024	100 %
Q 7 *When interacting with AI applications, have you been informed about its use?*		
A. Yes	1837	45.7 %
B. No	1096	27.2 %
C. I do not remember	1091	27.1 %
Q 7.1 *When were you informed about?*		
A. Before interacting	1304	32.4 %
B. After interacting	79	2 %
C. Before and after interacting	375	9.3 %
D. I do not remember	79	2 %
E. Non-response	2187	54.3 %
Q 7.2 What *were you informed about?* (Multiple answers are possible)		
A. How your personal data were expected to be used (Yes)	1112	27.5 %
B. How the AI application was used (Yes)	877	21.8 %
C. Why the AI application was used (Yes)	1298	32.3 %
D. The possibility to get further clarification about the AI application (Yes)	423	10.5 %
E. The possibility to object to the data processing being automatically done by the AI application, without the involvement of a human being (Yes)	344	8.6 %
F. Non-response	2187	54.4%
Q 7.3 *How was the information presented to you?*		
A. Orally	427	10.6 %
B. Written	1026	25.5 %
C. Orally and written	326	8.1 %
D. I do not remember	58	1.4 %
E. Non-response	2187	54.3 %
Q 8 *Could you opt out of the use of AI applications?*		
A. No	808	20.1 %
B. Sometimes	605	15 %
C. Yes	1071	26.6 %
D. I do not remember	448	11.1 %
E. Non-response	1091	27.1 %

Note: Own elaboration.

Table 3
Sensitive topics categorization following GDPR's article 9.

Sensitive topics	Frequency	Other topics	Frequency
Gender	47.34 %	Nationality	33.47 %
Racial and/or ethnic origin	14.81 %	Age	67.20 %
Disability	5.82 %	Family status	14.99 %
Sexual orientation	7.03 %	Address	16.20 %
Physical health	9.97 %	Education	44.51 %
Mental health	8.82 %	Previous working experience	38.54 %
Genetics	1.12 %	Gap years	4.5 %
Religion	4.85 %	Language(s) spoken	41.35 %
Trade union affiliation	1.39 %	Availability	24.60 %
Political affiliation	2.24 %	Other	15.63 %

Note: Own elaboration.

The list of items was developed collaboratively among the partners of the [removed for reviewing purposes] project to ensure it covered a comprehensive set of information categories. Importantly, the list was constructed to include items considered sensitive according to Article 9 GDPR, and an equal number of items not covered by this article and thus considered less or non-sensitive. This design makes it possible to examine differences in how respondents perceive and experience AI interactions depending on the sensitivity of the information requested, while also ensuring that the results of the regression analyses remain comparable by the same number of items underlying the construction of our two main dependent variables.

To model these outcomes, we used Poisson specifications, a type of generalized linear model that assumes the dependent variable follows a Poisson distribution. This choice was appropriate for our data, as the count variable did not exhibit over-dispersion, with the standard deviation being less than twice the mean.

For the independent variables, we first identify the type of AI interaction. This variable is dichotomous, with 0 (our baseline) corresponding to respondents who interacted with AI exclusively at the recruitment stage, and 1 representing those who interacted with AI exclusively in the workplace (*e.g.*, for training, improving performance, promotion, and sanctioning). To filter out noise, we removed from this part of the analysis all respondents who interacted with AI at both stages. This variable serves as our main independent variable, which interacts with all other independent variables to allow different coefficients for the impact of these other variables at different stages (both in recruitment and employment).

The additional variables capture different demographics that legal frameworks and scholarly literature consistently associate with potential grounds for discrimination (Rigotti & Fosch-Villaronga, 2024). These include gender, age, education, employment status, trade union membership, race, and a “subjective” measure of minority status based on respondents’ self-identification. For ease of interpretation, we dichotomized all these variables, assigning a value of 1 for the specific groups within each of these dimensions that we expect to face discrimination. Specifically, gender is coded as 1 for female and other genders (0 for male). For age, we coded as 1 for respondents over 40 years old; education is coded as 1 for people with tertiary education; employment status is coded 1 as for all employed and self-employed people (0 for unemployed). For trade union membership, members are coded as 1, non-members as 0. For race, non-white is coded as 1, white as 0. For the subjective criterion, those who consider themselves as part of a minority group are coded as 1, those who do not as 0.

To assess whether a random effects or fixed effects specification is more appropriate for modelling country-level clustering, we employ a

Mundlak-Chamberlain correlated random effects (CRE) test (Chamberlain, 1982; Mundlak, 1978). This approach is preferable to the classical Hausman test in nonlinear count data settings, as it does not require the random effects estimator to be fully efficient under the null hypothesis and is directly applicable within a Poisson framework (Wooldridge, 2010). The test augments the random effects specification with the country-level means of all covariates and evaluates whether these means are jointly significant. Significant group means would indicate that unobserved country-level heterogeneity is correlated with the regressors, violating the random effects assumption. We find no evidence of such correlation: the group means are jointly insignificant for both information-seeking about rights under GDPR ($\chi^2(8) = 5.32$, $p = 0.72$) and information-seeking from other sources ($\chi^2(8) = 3.28$, $p = 0.92$), supporting the use of random effects. This choice is further supported on substantive grounds: our sample spans 24 countries of residence with considerably unequal cluster sizes, ranging from single-digit observations in smaller countries to several hundred in larger ones. Fixed effects estimation would discard all between-country variation and produce unreliable estimates for small clusters. As a robustness check, we re-estimated all main models using the Mundlak-augmented CRE specification; the key coefficients of interest remain substantively unchanged (see Appendix B).

4. Results

4.1. Perceived transparency practices in AI-mediated interactions

The first part of the analysis examines perceived transparency practices, beginning with whether respondents were informed that they were interacting with an AI system. Slightly fewer than half of the respondents (45.6%) reported being informed, while 27.1% indicated they were unaware, and 27.2% unsure. Among those who acknowledged being informed about AI systems, they were then guided to two follow-up questions that tried to clarify the specifics of the information provided and the methods by which it was communicated.

As Table 4 shows, a substantially larger share of respondents who reported being informed were <40 years old (87%), compared to those aged over 40 (13%). This pattern may reflect generational differences in how each group interprets, understands, or recalls such AI-disclosures. Similarly, males (56%) were more likely to report being informed than females/other genders (44%). When looking at the type of interaction, individuals interacting with AI in the workplace reported significantly higher awareness (86%) compared to those in recruitment contexts (14%), suggesting that disclosure practices may be perceived as more developed in workplaces than recruitment or hiring environments. One possible explanation is that workplace interactions occur under established contractual relationships, while recruitment interactions are typically more limited and transactional, which may affect how disclosures are provided or perceived.

Regarding the timing of information, a majority of respondents (about 71% if non-response values are not accounted for) reported being informed before interacting with the AI system, while 20.4% of respondents received information before and after the interaction. 4.3% were unsure of the exact timing, and another 4.3% received information only after the interaction. These results are broadly consistent with the AI Act's emphasis on informing users about AI usage before interaction but also indicates room for improvement, given a non-negligible share who were either unsure or informed only post-interaction.

The content of the information provided also varied. While 60.5% of respondents were informed about data processing, 70.7% about why the technology was being used, only 47.7% were informed about how the AI applications worked. Fewer respondents received rights-based information: 23.0% were informed about the possibility to request additional information, and 18.7% about the complete automation of HR practices and the option to opt out. These findings indicate that procedural aspects of transparency are communicated more frequently and consistently than substantive justifications, such as the reasons behind AI use. Instead, rights-based information is reported far less often. This pattern may suggest that transparency practices tend to emphasize formal disclosure over supporting users' understanding with meaningful explanations.

In terms of delivery, more than half of the respondents (55.9%, if non-response values are not accounted for) reported receiving information in writing, while 17.7% of respondents received both oral and written explanations. Having multiple formats could either enhance understanding, by reinforcing key points, or create confusion if the messages are inconsistent or overly complex. A smaller proportion (3.2% of respondents) were uncertain about the delivery method.

Finally, when asked about the possibility of opting out of using AI systems, 36.5% reported having this option whereas 27.6% not, while 15.3% cannot recall. The remaining 20.6% said "sometimes" it was possible. The relatively high number of 'unsure' responses seems to indicate that opt-out mechanisms are inconsistently implemented or insufficiently unclear, including practices or hurdles (such as complex or relatively hidden interfaces). The inconsistencies in both information delivery and opt-out practices suggest that current approaches may fall short of enabling genuine user agency in the context of AI systems.

Overall, these findings indicate that while transparency measures are sometimes in place, they remain fragmented and procedural in nature. Moreover, these results reinforce the idea that transparency is not only about the formal provision of information, but also about ensuring that information is understandable, accessible, and actionable (Felzmann et al., 2020; Felzmann, Villaronga, et al., 2019).

4.2. Information requested by AI systems

The second part of the analysis examines the type of information

Table 4
When interacting with AI applications, have you been informed about its use?

Group	No	Yes	I do not remember	Chi-Pearson[b]
Gender	*p = 0.05*[a]	*p = 5.05e-07*	*p = 9.97e-07*	*p = 3.22e-12*
Male	47 %	56 %	43 %	Chi-Pearson (2) = 52.92
Female (and other)	53 %	44 %	57 %	V Cramer = 0.11
Age	*p = 1.93e-105*	*p = 9.99e-222*	*p = 2.00e-123*	*p = 8.87e-03*
< 40 years-old	83 %	87 %	86 %	Chi-Pearson (2) = 9.45
> 40 years-old	17 %	13 %	14 %	V Cramer = 0.04
Education	*p = 2.94e-40*	*p = 9.23e-80*	*p = 1.88e-42*	*p = 0.57*
< Bachelor's degree	30 %	28 %	29 %	Chi-Pearson (2) = 1.14
> Bachelor's degree	70 %	72 %	71 %	V Cramer = 0
Type of interaction	p = 1.37e-09	p = 2.54e-183	p = 9.09e-11	p = 2.73e-64
Recruiting only	40 %	14 %	40 %	Chi-Pearson (2) = 292.72
Workplace only	60 %	86 %	60 %	V Cramer = 0.29

[a] Differences within categories.
[b] Differences between categories.

Table 5
Dependent variable statistics.

	Mean	St Dev	Min	Max	Correlation[a]
Sensitive topics	1.03	1.45	0	10	0.48
Other topics	3.00	2.10	0	10	

Note: Own elaboration.
[a] Using pairwise complete observations.

respondents reported being asked to provide when interacting with AI systems. Table 5 summarizes descriptive statistics for the two dependent variables: the number of sensitive items and the number of non-sensitive items reported. Respondents, on average, reported being asked for more non-sensitive items compared to sensitive items in their experiences (mean = 3) than for sensitive information (mean = 1.03). However, responses varied widely: while some respondents report being asked for no information, others report being asked for all items, in both categories. A positive correlation between the two variables (r = 0.48) suggest that reported data collection tends to be cumulative rather than substitute: respondents who reported being asked for sensitive information also tended to report being asked for more non-sensitive data.

This pattern is also reflected in the correlation matrix between individual items in Q12 (*see* Fig. 1). The likelihood of respondents reporting be asked about a specific item is positively associated with nearly all other items, with no negative correlations observed. However, the strength of these associations varies. The stronger positive coefficients appear to cluster within thematic groups: basic demographic information (*e.g.,* gender, nationality, race, and family status), and professional background (including education, previous work experience, availability, age, and spoken languages). Correlations are consistently lower across these groups. For example, the weakest correlations are generally observed between professional background items and religion, political affiliation, and health-related items (generally between 0.03 and 0.15), which may reflect the fact that such information is less commonly requested in employment contexts due to its heightened legal sensitivity. Conversely, the highest coefficients are found within dimensions, such as between mental and physical health (r = 0.63), age and languages spoken (r = 0.59), gender, nationality, and age (r = 0.52), and education and work experience (r = 0.5).

To explore whether these patterns vary by demographic factors, we conducted a regression analysis using two dependent variables: the number of sensitive and non-sensitive items respondents reported being asked about. For the purpose of this analysis, we decided to use it as objective yardstick Article 9 GDPR, which prohibits the processing of personal data revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union membership, genetic data, biometric data for the purpose of uniquely identifying a natural person, data concerning health or data concerning a natural person's sex life or sexual orientation. Table 3 shows that items explicitly covered by Article 9(1) were classified as "sensitive"; and as "other" otherwise. We recognize that the context and circumstances in which information is processed are crucial factors in determining whether personal data should be considered sensitive under the GDPR, and that there may also be sensitive data that can be inferred from personal data in certain situations (Judgment of the European Court of Justice, Case C-184/20). For the purposes of this evaluation, however, only personal data that can be explicitly identified as sensitive is treated as such.

In Table 6, regression results show that, for sensitive topics, no meaningful differences were observed in the reported number of sensitive items between AI use in the workplace and during the recruiting stages: in both contexts, the predicted number of items asked is about the same, averaging around 1 at the population mean. There are some exceptions: young, white people, and those who do not consider themselves a minority, report a lower number of sensitive items asked in the workplace compared to the recruiting stage. Even then, these differences are very small and not statistically significant at the $p < 0.05$ level. The only variable consistently associated with a higher reported number of sensitive items is the subjective perception of being in a minority, and to

Table 6
Regression results.

	Sensitive topics	Other topics
Independent variables		
Type of interaction (*Workplace*)	−0.41*** (0.14)	−0.56*** (0.08)
Gender (*Female*)	−0.09 (0.07)	0.04 (0.03)
Age (*Older cohort*)	0.01 (0.10)	0.06 (0.05)
Education (*High education*)	−0.13* (0.07)	0.02 (0.04)
Employed	0.01 (0.11)	−0.03 (0.05)
Trade union	0.04 (0.13)	0.10 (0.06)
Race (*Non-white*)	0.07 (0.12)	−0.04 (0.06)
Minority	0.05 (0.10)	0.10* (0.05)
Interactions		
Workplace * Female	0.10 (0.08)	−0.05 (0.04)
Workplace * Older cohort	0.13 (0.11)	−0.01 (0.06)
Workplace * High education	0.08 (0.08)	−0.01 (0.05)
Workplace * Employed	0.18 (0.13)	0.17** (0.07)
Workplace * Trade union	0.12 (0.14)	−0.05 (0.08)
Workplace * Non-white	−0.12 (0.14)	0.14* (0.08)
Workplace * Minority	0.24* (0.12)	0.00 (0.07)
Constant	0.10 (0.12)	1.26*** (0.06)
N	3294	3294
Prob > chi2	0.00	0.00
Log likelihood	−4698.35	−6500.98

Note: Poisson regression.
***: p-value <0.01, **: p-value <0.05, *: p-value <0.1. Own elaboration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Genetics (1)																	
Trade Union Aff. (2)	0.11																
Religion (3)	0.11	0.23															
Political Aff. (4)	0.08	0.34	0.40														
Gap Years (5)	0.02	0.11	0.10	0.10													
Availability (6)	0.03	0.06	0.06	0.06	0.13												
Address (7)	0.05	0.10	0.12	0.08	0.13	0.24											
Education (8)	0.04	0.07	0.15	0.12	0.14	0.25	0.29										
Work Experience (9)	0.04	0.05	0.05	0.09	0.22	0.33	0.28	0.50									
Disability (10)	0.13	0.12	0.22	0.18	0.15	0.15	0.17	0.15	0.15								
Physical Health (11)	0.11	0.14	0.25	0.21	0.09	0.09	0.09	0.12	0.09	0.33							
Mental Health (12)	0.09	0.15	0.26	0.23	0.08	0.08	0.05	0.11	0.09	0.34	0.63						
Age (13)	0.03	0.04	0.13	0.09	0.08	0.15	0.23	0.33	0.23	0.14	0.16	0.14					
Languages Spoken (14)	0.03	0.05	0.14	0.13	0.11	0.31	0.25	0.36	0.36	0.16	0.12	0.12	0.59				
Gender (15)	0.03	0.05	0.18	0.11	0.06	0.10	0.25	0.25	0.14	0.17	0.16	0.15	0.52	0.22			
Nationality (16)	0.04	0.06	0.22	0.15	0.10	0.16	0.32	0.30	0.22	0.18	0.14	0.14	0.42	0.26	0.51		
Family Status (17)	0.08	0.12	0.28	0.20	0.11	0.17	0.32	0.23	0.18	0.25	0.24	0.25	0.26	0.20	0.30	0.37	
Race (18)	0.07	0.09	0.34	0.24	0.13	0.13	0.16	0.21	0.15	0.31	0.23	0.24	0.25	0.19	0.39	0.44	0.35

Fig. 1. Correlation matrix between different components of Q12
Note: Own elaboration.

a lesser extent race, which is associated with a higher number of reported sensitive information.

For non-sensitive topics, differences between recruitment and workplace settings are more pronounced. The predicted number of non-sensitive items reported during recruiting is about 3.75, while at the workplace it is 2.5 (see Fig. 2). The difference between the two is statistically significant at $p < 0.001$, as shown in the regression results in Table 6.

Despite this difference, even the lower number of non-sensitive topics asked in the workplace is still much higher than the number of sensitive topics asked at any stage, since the predicted number for sensitive topics is about 1 out of ten items (see Fig. 3). Once again, subjective perceptions of minority status are relevant at both the recruitment stage and in the workplace, where they are positively correlated with being asked for information. Non-white people follow a similar pattern at the workplace, but this difference is not statistically significant at $p < 0.05$.

These findings indicate that respondents report being asked for considerably more non-sensitive information than sensitive information, particularly in recruitment contexts. Importantly, objective characteristics such as gender and age, do not seem to affect the predicted number of items asked. The most consistent predictor is the subjective perception of belonging to a minority group. Because our data capture reported perceptions and experiences rather than records of what AI systems actually asked, this pattern admits of more than one interpretation. It is possible that minority-identifying individuals are subject to more frequent requests for sensitive data. However, it is equally plausible - and more consistent with the legal prohibition on differential treatment on the basis of protected characteristics under EU law - that the same questions are asked of all candidates, but are experienced and recalled differently depending on personal characteristics and lived experience. The data cannot distinguish between these mechanisms, and this limitation is addressed in the discussion.

5. Discussion

5.1. Awareness gaps in AI-mediated interactions

Our discussion begins by revisiting respondents' awareness of AI systems in recruitment and employment, a central aspect of transparency examined in this study. Nearly half of the respondents reported immediately recognizing that they had interacted with an AI system in recruitment or employment contexts. However, a notable proportion only recognized their interaction with AI after being prompted with some examples of widely used platforms and applications included in the survey questionnaire. This finding may suggest that awareness of AI use is often contingent on how such systems are framed or described. In other words, despite AI's expanding presence, its use is not always immediately recognizable by job applicants and workers, exposing a gap between lived experiences and awareness of when AI is involved in employment-related interactions. This mirrors Büchi et al.'s (2023) observation that algorithmic profiling often remains opaque to users despite its ubiquity and hype. This pattern is evident given that 86% of respondents were under 40 - an age group generally considered more digitally literate - and 72.9% held a higher education degree. The fact that even these groups demonstrated limited awareness suggests that technological nativity and formal education alone may be insufficient, on their own, to ensure awareness of when AI is used in recruitment and workplace operations.

Gender differences further complicate this picture. Our findings indicate that female respondents, as well as those identifying with other gender identities (totaling 44%), were more likely to report being unaware of their interactions with AI, aligning with previous research on the persistent gender digital divide (Martínez-Cantos, 2017; Wajcman & Young, 2023). These respondents were also more likely to revise their initial responses after being shown examples, which may reflect differences in interpretations on what counts as 'AI' or 'AI use' or differences in how such interactions are recalled. These disparities may also relate to broader structural factors discussed in the literature, including gendered differences in confidence in engaging with digital tools, potentially due to their structural exclusion from technology design and decision-making processes (Dijk, 2020). This highlights the importance of transparency practices that go beyond generic notices and provide context-specific, actionable information about when and how AI systems are used in recruitment and employment, in line with previous research (Armstrong et al., 2023).

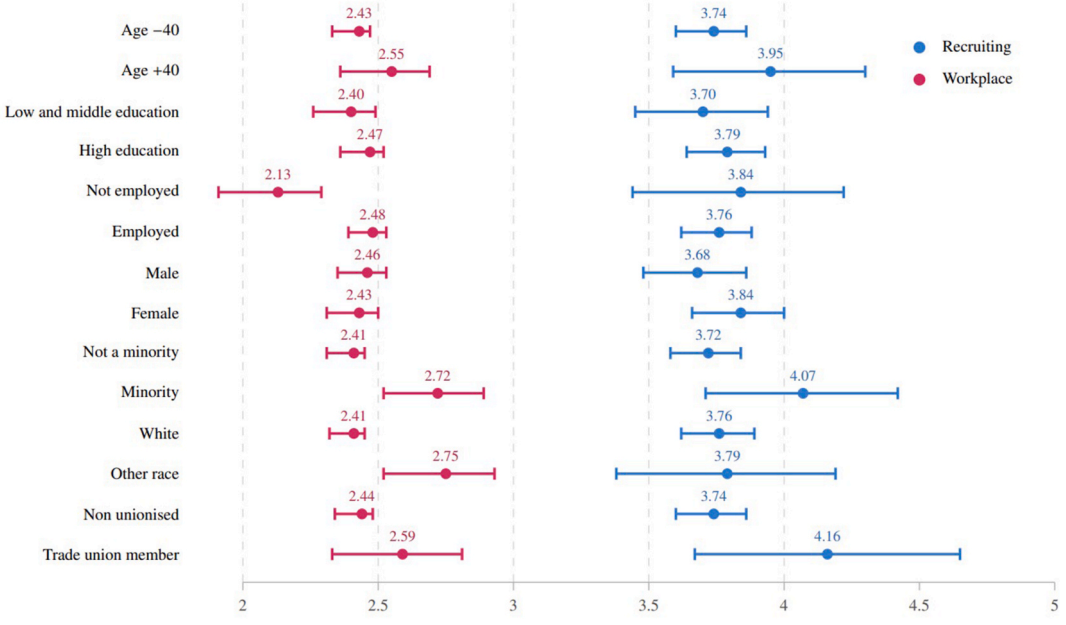

Fig. 2. Predicted count for other topics
Note: Own elaboration.

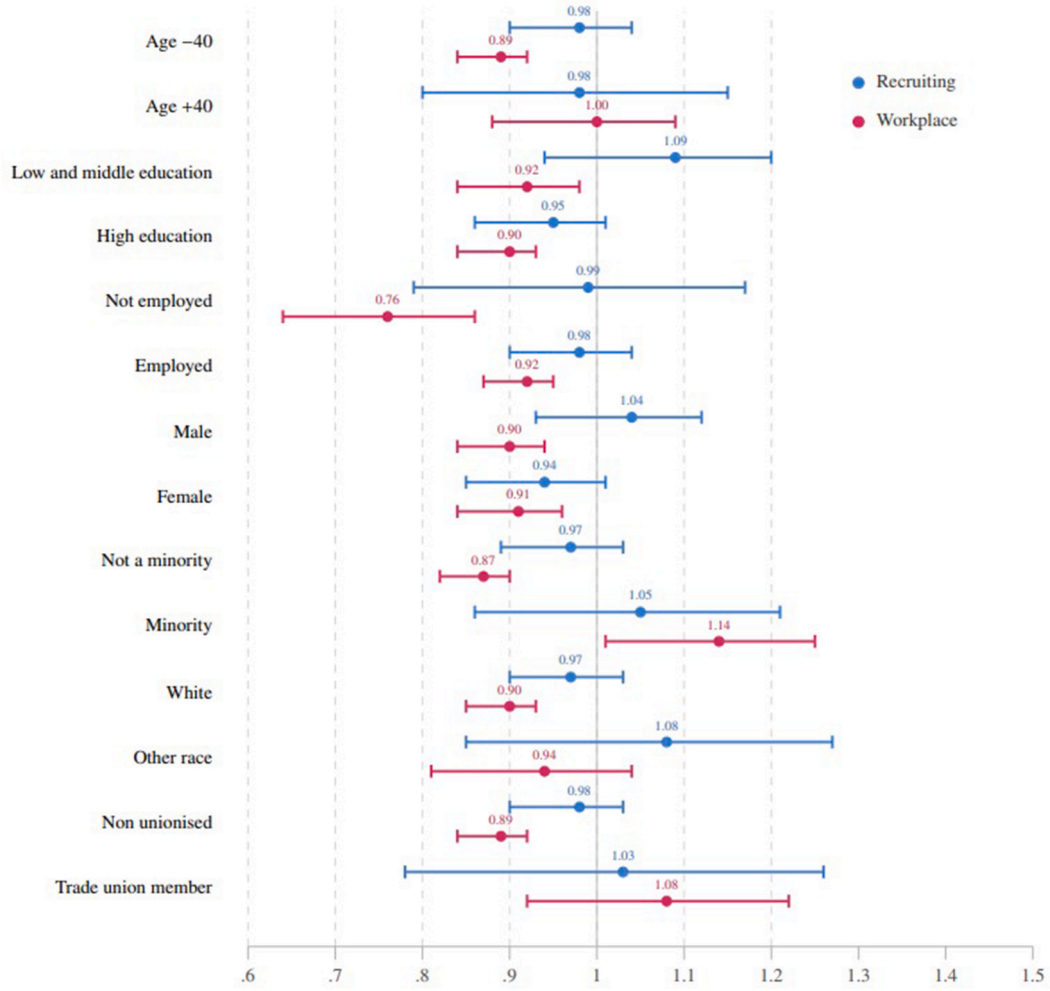

Fig. 3. Predicted count for sensitive topics
Note: Own elaboration.

5.2. *The limits of transparency practices*

In exploring how job applicants and workers experience AI transparency, our findings reveal a significant transparency gap in recruitment and employment, with many respondents either unaware of AI use or unsure whether it was involved. Among those who were informed, the majority reported receiving information in written form and prior to any interaction, an approach that reflects early and formal disclosure obligations in Articles 13 and 14 GDPR. This pattern suggests that transparency practices often rely on standardized data protection notices or consent forms, which tend to emphasize procedural compliance rather than meaningful communication (Felzmann, Villaronga, et al., 2019). While written materials provide a lasting reference, research on informed consent emphasizes that oral explanations allow for clarification and questions, thereby supporting genuine understanding (Schenker et al., 2011). This is especially important when AI systems influence high-stakes employment outcomes such as shortlisting, promotion, or dismissal. The effectiveness of transparency practices thus depends not only on the provision of information but also on the clarity, consistency, and accessibility of the communication. We argue that written disclosures, when enriched with clear, context-specific explanations of how AI systems are designed and deployed, can help job applicants and workers better understand their rights and encourage them to seek clarification. For instance, such transparency can enable individuals to recognize when an automated screening system rejects an application in a potentially biased or discriminatory manner, situations that might otherwise remain opaque (Lytton, 2024).

Simultaneously, transparency efforts must contend with the risk of 'transparency fatigue' (Draper et al., 2024), where overly detailed or frequent disclosures overwhelm users and deter meaningful engagement. A related concern is the 'illusion of control' (Molavi Vasse'i & McCrosky, 2023) in which information is provided but remains too complex or abstract for individuals, particularly those lacking AI literacy, to interpret or act upon. This highlights the importance of complementing legal compliance with communication strategies tailored to users' needs and capacities, so that transparency becomes comprehensible and actionable. Lessons from consumer and data protection law show that transparency is most effective when it is user-centered, context-specific, and empowers individuals - in the instant case job applicants and workers - to act on the information provided, rather than simply fulfilling formal disclosure requirements (Hacker & Passoth, 2022). In HR settings, this also means aligning transparency with employment relations, power asymmetries, and the practical realities of workers' ability to understand and contest decisions.

Our results show that respondents were most frequently informed about procedural aspects, such as, AI functionality, data processing and the rationale for AI use, while rights-based information, particularly about the ability to seek further information and opt out, was far less common. This pattern raises two distinct concerns. First, it raises questions about the practical effectiveness of Article 21 GDPR in enabling individuals exercise their right to object to processing, and which Section 2.2 ("Transparency at work under the GDPR and the AIA") identifies

- drawing on relevant literature - as one of the GDPR provisions instrumental in ensuring transparency. Second, it suggests that transparency obligations may be oriented more toward formal compliance than toward empowering job applicants and workers to exercise meaningful control. These results echo wider concerns in the literature that formal compliance with transparency rules, such as issuing privacy notices, does not necessarily translate into meaningful user control or accountability (Edwards & Veale, 2018; Kroll et al., 2017). Similarly, Wachter et al. (2017) highlight that even when rights, such as opting out, exist on paper, practical and procedural barriers often prevent individuals from exercising them effectively, a problem that might be particularly acute in the employment relationship due to fear of retaliation or negative career consequences.

Transparency, therefore, should not be conceived as a one-off disclosure, but as a dynamic and continuous process that supports individuals throughout their interaction with AI systems - a perspective that aligns with the literature discussed in Section 2.1 ("Transparency in the datafied workplace"). Beyond fulfilling the traceability and explainability obligations in data protection law or AIA, effective transparency must equip job applicants and workers with actionable knowledge, while also enabling employers and HR practitioners to engage responsibly with these systems. Achieving this requires accessible, relevant, and context-specific information, and institutional safeguards that account for varying levels of AI literacy and demographic disparities in digital engagement. Without these measures, formal transparency risks remaining a procedural formality rather than functioning as a safeguard for protecting agency and rights in the datafied workplace.

5.3. Diversity bias in data processing

Zooming in on the types of personal information requested by AI systems, our findings reveal disparities in reported data-collection experiences across gender, age, and education. These patterns are consistent with broader concerns that datafied HR practices may interact with pre-existing social hierarchies, rather than operating in a socially neutral way (Rigotti & Fosch-Villaronga, 2024). They also challenge the often-repeated claim that AI necessarily enhances objectivity in recruitment and employment decisions (Black & van Esch, 2020; Cowgill, 2019; Horodyski, 2023) noted in the Introduction. This issue is particularly significant because most of these data-collection practices occur at the hiring stage, rather than as part of a broader HR management. This highlights the early-stage filtering function of AI, and potentially invasive role, in determining access to job opportunities. Moreover, while the dominant critique of AI systems in recruitment and employment has focused on the risk of discrimination resulting from biased training data (Köchling & Wehner, 2020), our findings point to a different but equally important direction: differential data collection practices can shape how job applicants are profiled from the outset, even before algorithmic decision-making occurs. That said, it is important to emphasize that our respondents did not interact with a single standardized AI system, and - to the best of our knowledge - there is no publicly documented system that systematically operationalizes such data-gathering practices. This underscores the need for future empirical research, to investigate whether and how specific AI systems adopt differentiated data collection strategies and to assess how such practices affect trustworthiness fairness, and compliance with data protection principles, particularly those in Article 9 GDPR on sensitive data.

Our regression results shed further light on how demographic factors shape reported perceptions and experiences of AI interactions, with important caveats about interpretation. Women reported being asked more frequently about their mental health and previous work experience than men. Because the data are self-reported and do not capture the underlying behavior of specific AI systems, this pattern cannot be interpreted as evidence that AI systems direct different questions to different demographic groups. Under EU anti-discrimination law, directing different questions to job applicants on the basis of protected characteristics would risk constituting direct or indirect discrimination, making differential system behavior of this kind legally problematic, even if not explicitly prohibited in the form of a uniform questioning requirement. Combined with the limitations of self-reported data, this makes differential system behavior an implausible and empirically unverifiable explanation for the observed pattern. A more plausible and theoretically grounded interpretation is that the same questions are experienced with different degrees of personal relevance depending on the respondent's social position. Questions about mental health, family status, or career gaps may carry different subjective weight for women than for men, not because the question was framed differently, but because the social consequences of those questions are distributed unequally. Women are statistically more likely to experience mental health conditions such as depression (WHO, 2023), more likely to have had career interruptions associated with caregiving responsibilities (Weldon-Johns, 2021), and may therefore more readily anticipate that such information could be used against them in hiring decisions. Under these conditions, heightened attention to and recall of sensitive questions is precisely what one would expect, and is itself a meaningful indicator of how existing social inequalities shape the experience of AI-mediated interactions, even when system behavior is formally identical across groups.

Similar dynamics appear across other demographic dimensions. Reported questions about mental health decrease with age, consistent with generational differences in attitudes towards mental health disclosure (ESCAP, 2022), while older respondents more frequently reported questions about family status and work experience and younger respondents about educational background, reflecting age-related expectations about career stage that AI systems may operationalize and reinforce. Education follows a comparable logic: higher formal qualifications appear associated with fewer questions about age and physical health, suggesting that credentials function as a proxy for employability that partially shields individuals from certain forms of scrutiny, even as questions about work experience increase.

These patterns collectively indicate that AI-driven data collection does not occur in a social vacuum, but rather interacts with and reflects existing social hierarchies and expectations. This is consistent with the literature on AI bias discussed in Section 2.1 ("Transparency in the datafied workplace") and highlights the close relationship between transparency and fairness: if the experience of AI-mediated interactions is itself shaped by structural inequality, transparency obligations that treat all recipients as equivalently positioned will systematically fall short. Proactive safeguards in both system design and regulatory oversight are needed, not only to prevent discriminatory data collection practices, but to ensure that transparency mechanisms are attuned to the various stakes and vulnerabilities of those they are meant to protect.

5.4. Towards AI literacy and transparency-by-design

A central lesson from our findings is the importance of improving AI literacy as a way to bridge current awareness gaps and support more informed engagement with AI systems. Evidence from the CEDEFOP survey (2024) shows that while many workers recognize the need to upskill in response to AI's growing presence in their jobs, they often doubt that employers will provide adequate training. The relevance of AI literacy is also reflected in Article 4 AIA, which requires providers and deployers to ensure that their personnel have appropriate level of understanding based on the system's context. Complementing this, Article 3(56) AIA defines AI literacy as the combination of skills, knowledge, and understanding needed to make informed decisions about AI use, including awareness of its opportunities, risks, and harms. This broader framing suggests that AI literacy may also encompass understanding data processing and transparency obligations, empowering individuals to recognize when and how their data is collected and used in line with the GDPR's framework outlined in Section 2.2 ("Transparency at work

under the GDPR and the AIA"), as well as how AI systems shape recruitment and employment decisions.

As mentioned in the subsection above, our findings indicate that even digitally literate and highly educated cohorts struggle to recognize or understand AI use, reinforcing the need for targeted upskilling efforts and context-specific training to enable individuals to exercise their rights effectively. In concrete, AI literacy can help job applicants and workers identify when they are subject to AI-driven decision-making and better exercise their data protection rights. Importantly, this does not imply a shift of responsibility onto individuals, a limitation long recognized as a shortcoming of EU data protection law (Aloisi, 2024; Choi et al., 2018). Rather, AI literacy can complement regulatory safeguards by enabling individuals to recognize AI-mediated decision--making and, where possible, better exercise their rights. Also, the AIA only provides that where a decision is made using a high-risk AI system that significantly affects a person's health, safety, or fundamental rights, that individual has the right to receive a clear explanation of the role played by the AI system in the decision-making process pursuant to Article 86. Still, targeted upskilling efforts, such as those promoted by various EU initiatives such as [omitted for reviewing purposes], can equip individuals to critically engage with AI systems, challenge adverse outcomes, and understand the broader implications of automation in their working lives. Supporting this form of empowerment is essential to mitigating harm and fostering a more informed and resilient workforce (Bankins et al., 2022; Cetindamar et al., 2024).

However, our findings also suggest that AI literacy alone is insufficient to ensure meaningful transparency, particularly given how information is currently being provided and experienced by workers. In this sense, prevailing understandings of meaningful transparency often fail to account for the structural inequalities of the labor market that shape how different groups encounter and interpret AI-mediated decision-making (Rigotti & Fosch-Villaronga, 2024). We therefore argue for a complementing 'transparency-by-design' approach (Felzmann et al., 2020; Zieglmeier & Pretschner, 2023), one that integrates transparency into the design, development, and deployment of AI systems. This approach should engage with a representative group of stakeholders, including job applicants, workers, employers, trade unions, and HR practitioners. It should also align with GDPR and AIA provisions in a way that is dynamic and context-sensitive. In this way, this engagement could situate technical decisions within the lived realities of those affected and within broader social and organizational hierarchies, while fostering genuine trust and moving beyond mere 'transparency-washing'.

Transparency, in this sense, and in line with the existing body of literature mentioned in Section 2.1 ("Transparency in the datafied workplace"), should not be a one-off disclosure but a continuous process that includes clear documentation of how datasets are constructed, what normative assumptions inform decision-making, and where sources of bias or uncertainty exist. It should also entail disclosing how data are collected and processed, which AI systems are involved, when and how human oversight takes place, and what risks are associated with the system's use. Importantly, transparency must illuminate the reasoning behind inferences drawn by AI systems and clarify whether these are justified and aligned with the system's intended purpose. This visibility not only supports accountability and trust but also enables job applicants and workers to understand how their data are used, how decisions are made, and what steps have been taken to minimize potential harms such as data protection violations or discriminatory outcomes. Embedding these measures from the outset can help to foster genuine accountability and trust, ensure that transparency obligations move beyond formal compliance rather than being reduced to box-ticking exercises - as shown by Nieuwenhuizen (2024) in the context of algorithm registers - and meaningfully support a more inclusive deployment of AI in the workplace.

5.5. Limitations and future research

As with any empirical study, our analysis has several limitations that should be considered when interpreting the results. A first limitation concerns the demographic composition of the sample, which consists primarily of younger and highly educated individuals. While these cohorts are substantively relevant – being more likely to interact with AI systems during job search and workplace settings, and statistically necessary to ensure sufficient variation for robust analysis – the experiences and perceptions of older and less formally educated populations, as well as people who have different demographics remain underrepresented in this study. These groups may face distinct barriers to recruitment or employment and could be profiled differently by AI systems, highlighting the need for further research.

A second limitation is that our survey design does not differentiate between specific AI systems or applications in the labor market. This limits our ability to assess whether specific technical designs or system functionalities are associated with specific transparency practices or data collection patterns. These distinctions could reveal whether certain systems are more likely to engage in problematic practices. While this differentiation could offer critical insights that merit dedicated future research, incorporating it into the present survey design would have necessitated nevertheless a much narrower methodological focus, one that would conflict with the broader aim of the [omitted for review purposes] project. Nonetheless, future research could examine AI implementation perspectives across diverse HR functions to better capture the task-specific risks and transparency challenges of these technologies. Relatedly, the absence of a formal definition of AI and the use of concrete examples to anchor respondents' interpretations means that the study measures reported awareness rather than verified AI exposure. Some respondents may have recognized AI use only after encountering the examples provided, which introduces a degree of instrument sensitivity that future research using validated AI literacy measures could address.

Third, the study design does not allow for causal inference and the findings should therefore be interpreted as descriptive and correlational. While this limits our ability to draw conclusions about causal mechanisms, the analysis nonetheless provides empirically grounded insights into how AI transparency is experienced in practice and how these experiences relate to existing regulatory and policy debates.

Finally, the study does not examine cross-country and sector-specific variations. Given the uneven implementation of EU-level norms and the diversity of labor market structures, comparative research, both qualitative and quantitative, could provide crucial insights into how institutional and professional contexts shape AI awareness, transparency practices, and worker experiences. Future work combining large-scale surveys with qualitative methods would be particularly valuable in capturing these contextual dynamics and their implications for fairness and transparency.

6. Conclusion

In examining how transparency is, and should be, interpreted and operationalized in the context of AI systems in the labor market, this study underscores that ensuring meaningful transparency requires more than formal compliance with GDPR and AI Act obligations: it requires grounding legislation in the lived experiences and perceptions of those most affected. By analyzing the perspectives of over 4000 job applicants and workers, we directly address our first research dimension - awareness of AI-mediated interactions - and find a substantial transparency gap, highlighting that existing transparency mechanisms often fail to achieve their core regulatory purpose of enabling job applicants and workers to recognize, understand, question, and contest AI-driven decision-making. Our second research dimension - exposure to sensitive data collection - reveals equally troubling patterns, suggesting that AI-driven data practices may not be neutral but shaped by, and can

reinforce, existing social inequalities, thereby creating risks of differential treatment in the workplace.

Our findings demonstrate that effective technology regulation should more heavily rely on empirical research that captures how AI systems are experienced in practice (Khan et al., 2023; Papagiannidis et al., 2023). Surveys like ours provide insights that cannot be obtained through legal analysis or technical assessment alone, revealing how job applicants and workers actually perceive and are affected by AI in recruitment and workplace settings. This type of evidence is indispensable for developing regulatory measures that are not only legally sound but also socially grounded and responsive to real-world impacts. This approach advances what we call *Science for Tech Policy*, an approach already applied in areas such as robotics (Fosch-Villaronga et al., 2025), as our study illustrates how systematic, data-driven methods can meaningfully inform more context-sensitive and socially responsive governance of AI systems.

While AI literacy initiatives and transparency-by-design approaches remain valuable tools, responsibility must not rest with individuals alone. Ensuring meaningful transparency requires sustained engagement by employers, developers, and regulators to ensure that transparency is meaningful, actionable, and embedded throughout the AI lifecycle. This includes greater integration, and mutual reinforcement, of GDPR and AIA requirements. This entails striking an adequate balance between the right to information of job applicants and workers under Articles 12–14 GDPR, the detailed transparency obligations concerning AI system design, limitations, and risks, primarily set out in Articles 13 and 50 of the AIA; and their situation within the broader scholarly discourse on AI transparency, including the empirical evidence presented here.

Ultimately, by addressing who is aware of AI-driven interactions and who is exposed to sensitive data collection, our study demonstrates that perceptions matter for policymaking. Understanding how workers and job applicants experience AI is not a secondary concern but a prerequisite for building trustworthy and rights-respecting AI governance in the labor market.

CRediT authorship contribution statement

Carlotta Rigotti: Writing – original draft, Project administration, Investigation, Conceptualization. **Daniel Alves Fernandes:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis, Data curation. **Antoni Mut Piña:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Eduard Fosch-Villaronga:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Ethics approval

This study was performed in line with the General Data Protection Regulation and approval was obtained from the ethics committee of the coordinating university of the BIAS Project, the Norwegian University of Science and Technology (NTNU), and the Norwegian Data Protection Authority in April 2023.

Consent

Informed consent was obtained from all individual participants included in the study.

Transparency in the datafied workplace

Law, workers, and job applicant perspectives.

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Declaration of competing interest

The author(s) declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in the submitted paper *Transparency in the Datafied Workplace: Law, Workers, and Job Applicant Perspectives*.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2026.103387.

Data availability

Data are under embargo. Once approved by the European Commission, they will be publicly available on Zenodo via the BIAS project, with full documentation.

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