Received: 14 November 2020 | Revised: 21 November 2022 | Accepted: 2 February 2023

DOI: 10.1111/1748-8583.12499

SPECIAL ISSUE ARTICLE

Human Resource Management Journal WILEY

Digitalization and inclusiveness of HRM practices: The example of neurodiversity initiatives

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Abstract

The transformation of the intelligence ecosystem associated with the digital transformation represents a critical juncture for diversity and inclusion (D&I). We present a multidisciplinary perspective on digital transformation and D&I that demonstrates that, in the context of automated decision making, where algorithmic biases and the standardisation of thought represent new risks, neurodiversity initiatives become a cornerstone for advancing D&I. Based on interviews with neurodiversity experts, we identify innovative ways to efficiently configure an inclusive organisational design targeting neurodiversity by leveraging technologies. We identify several properties of technologies that support D&I in neurodiversity initiatives: the neutralisation of biases during interviews, the development of digital support for physical and mental well-being and the facilitation of different cognition modes. Finally, we critically discuss the risks and opportunities offered by various technologies in terms of performance evaluation, new forms of dominance, and design of a digital ecosystem for mental well-being.

KEYWORDS
digital transformation, digitalisation, disability, discrimination, diversity, neurodiversity

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Abbreviations: ADHD, attention deficit hyperactivity disorder; AI, artificial intelligence; AR, augmented reality; ASD, autism spectrum disorders (ASD); D&I, diversity and inclusion; VR, virtual reality.

Practitioner notes

What is currently known?

- The rebalancing between human and artificial intelligence represents a critical juncture for diversity and inclusion.
- The cognitive, data and socio-economic biases embodied in algorithms generate new exclusion mechanisms.
- Norms of abilities/disabilities are a social construct that is evolving during digital revolutions.
- Neurodiversity initiatives innovate by combining productivity gains with inclusion.

What this paper adds?

- A multidisciplinary perspective combining studies on disability, IT, economics, and HRM to demonstrate the coevolution between digital transformation and D&I.
- An analysis of properties of technologies that favour an inclusive organisational design targeting neurodiversity.
- The importance of mental health management as part of D&I policies and how technologies may support it.

Implication for practitioners

- Digital technologies strongly complement neurodiversity initiatives to design a new intelligence ecosystem at work.
- Various technologies can be leveraged to improve inclusiveness of recruitment, training, digital supervision, flexible workspaces and mental health policies.
- Algorithmic biases and privacy risks must be evaluated through the lens of equity.

1 | INTRODUCTION

In the 1960s, Polanyi (2009) stated that the phrase 'we know more than we can say' refers to the complexity and value of tacit knowledge, which is an element of human intelligence. The current digital transformation, also called the fourth industrial revolution (Schwab, 2017) represents a paradigm shift given that it encodes tacit knowledge and makes it visible. In a context in which individuals' interactions with technologies perpetually generate digital footprints, abundant, ubiquitous, and valuable data on human behaviour are accumulated and reflected by digital technologies. Therefore, digital technologies are intrinsically blended with human actions and behaviours and cannot be separated from them as a reflection on a mirror. As Schwab (2017, p. 106) argued, the fourth industrial revolution is not an exogenous force over which we have no control but is instead an invitation to reflect on who we are and how we perceive the world. In our view, it encodes and embodies the current state of decision making. As such, it provides an interesting tool to understand the mechanisms of discrimination and exclusion in the workplace and to correct them appropriately. In 2015, Amazon, for instance, discontinued its artificial intelligence (AI) based candidate evaluation tool used to assist HR services because it encoded discriminatory behaviours against women in the applicant ranking. This AI tool provided a useful snapshot for recognising discriminatory patterns in CV sorting, selection, and ranking.

Our study analyses how digital technologies are linked with diversity and inclusion (D&I) in the workplace by analysing the role technologies play in neurodiversity initiatives. Nkomo et al. (2019) pointed out that the D&I management literature is at a critical juncture due to contextual shifts in society related to the evolution of the socio-political context. This paper contributes to rethink the ontology of diversity by contextualizing it in the digital transformation, which raises two underlying general questions: Can technologies create new mechanisms of inclusion and exclusion? Can they neutralise discrimination behaviours and/or generate new forms of discrimination? To answer these questions, we provide a multidisciplinary analysis that is missing in the D&I management literature, which highlights the coevolution of D&I and digital transformation in the context of neurodiversity initiatives. This analysis is original because it builds theoretical bridges between different academic disciplines related to the economics of discrimination, disability studies and algorithm literature that have developed separately from the D&I management literature to explain discriminatory behaviours, stereotypes, or D&I as part of the same phenomenon. In the current context of rising algorithmic management and automated decision making (Duggan et al., 2020), the automation of inequalities may become unsustainable if inclusive HR practices do not support the digital transformation of workplaces (Crawford et al., 2019; Eubanks, 2018; O'Neil, 2016). By contextualising research on the use of technologies within neurodiversity initiatives, our study identifies pathways to connect technological change with D&I in the workplace.

Our analysis focuses on neurodiversity initiatives that have been overlooked in the D&I literature. The neurodiversity paradigm acknowledges perceptive, cognitive, and learning differences between individuals. It frames the heterogeneity and broad spectrum of neurocognitive functioning and human thought as diversity, as opposed to pathologising it as a disability, which is viewed as a deviation from the norm. Dyslexia, dyspraxia, dyscalculia, Attention Deficit Hyperactivity Disorder (ADHD), and Autism Spectrum Disorders (ASD) are lifelong conditions included in the neurodiversity paradigm, representing 10%–20% of the population when all different conditions are added (Doyle, 2020). Neurodiverse employees are a group subject to extreme discrimination. For example, in 2020, 34% of autistic workers in Australia were unemployed, compared to 10% of workers with disabilities and approximately 4% of those without disability (Hedley et al., 2022). Similarly, the labour force participation rate for autistic workers at 38% was amongst the lowest, compared to 53% for the population with disabilities or 84% for workers without disabilities (Australian Institute of Health and Welfare, 2020).

Neurodiversity initiatives represent an emerging global trend in management (Austin & Pisano, 2017). Despite their high adoption in the technology industry, little is known about the role of technologies in workforce neurodiversity. Walkowiak (2021) showed that technologies can be leveraged to improve the efficiency of employment programmes targeting autistic workers at the individual, organisational, and macroeconomic levels. In this study, we deepen the analysis of the links between the organisational design of neurodiversity and technology use to identify innovative ways by which technologies can drive inclusion. We show that neurodiversity offers a universal paradigm to overcome the conceptual dichotomies in the current D&I literature (Nkomo et al., 2019). We emphasise that analysing neurodiversity initiatives raises the important and universal question of the intersectionality of mental health and inclusion, which is often overlooked in the D&I literature.

The remainder of this paper is organised as follows. Section 2 provides a multidisciplinary perspective on D&I in the context of digital transformation. It shows that the physical and digital environments reflect each other, as a reflection on a mirror, and are governed by similar mechanisms of discrimination, by analysing the literature on digital disability, digital divide, and algorithmic bias. Section 3 demonstrates the significance of the neurodiversity paradigm for D&I and analyses the digital dimension of the organisational design of neurodiversity based on the qualitative research results. Section 4 discusses our findings and analyses the duality of technologies that can be used to promote inclusion.

2 | A MULTIDISCIPLINARY PERSPECTIVE ON THE DIGITAL TRANSFORMATION AND D&I

An important structural transformation of workplaces associated with neurodiversity management and digital transformation is work reorganisation, which relies on the fragmentation and reaggregation of physical, cognitive, information processing, and interpersonal tasks. This section reviews the literature on disability studies, economics, IT, and HRM, and shows that this evolution and changing division of labour is not neutral and can generate new mechanisms of inclusion or exclusion relevant to the D&I management literature. This multidisciplinary literature review highlights how physical and digital environments are governed by similar mechanisms in terms of D&I. On the one hand, Section 2.1 presents the concept of digital disability and literature on the digital divide to illustrate how the disabling environment of the physical world extends to a digital environment (Ellis & Kent, 2017; Goggin et al., 2003; Roulstone, 2016). On the other hand, Section 2.2 reviews the literature on algorithmic biases to illustrate how the digital environment creates new barriers to job access. Finally, Section 2.3 underlines the role of neurodiversity initiatives in the coevolution of D&I and digital transformation.

2.1 | Disability studies and the process of technological standardisation

In disability studies, the new concept of digital disability (Goggin et al., 2003) signals that individuals who are not using ICTs, digital platforms, or social media would find themselves effectively disabled due to a lack of access to information and communication (Ellis & Kent, 2017). This echoes the concept of digital divide, which has been extensively studied in different disciplines since the rapid computerisation of workplaces during the 1990s (Antonelli, 2003; Dimaggio et al., 2004; Helsper, 2021). In their recent systematic literature review on the digital divide, Lythreatis et al. (2022) distinguished three levels of digital divide. The first-level digital divide separates people in terms of access to technologies (computers, the Internet, and mobile phones) (Antonelli, 2003; Dimaggio et al., 2004). Access barriers are associated with physical infrastructure. The second-level digital divide separates people in terms of access to content, knowledge, or skills (Dijk, 2019). Barriers to access are informational and relate to human capital in the use of technologies. These barriers are less tangible than the physical infrastructure at the previous level. The third-level digital divide relates to the capacity to generate positive outcomes from access to technology (van Deursen & Helsper, 2015). For example, Johnson and Stone (2019) underlined that the use of e-recruitment tools in the context of the digital divide can negatively impact the employment opportunities of some groups, which can deteriorate D&I in the workplace. Moreover, social and digital inequalities are deeply intertwined. Lythreatis et al. (2022) synthesised numerous factors affecting the digital divide: sociodemographic, socioeconomic, personal elements (such as trust, privacy, and risk perception of technologies), social support, type of technologies, training, and events (such as the COVID-19 pandemic).

In conclusion, digital divide literature shows that access barriers in the physical world are reproduced in a digital environment (Dijk, 2019; Dimaggio et al., 2004; Goggin et al., 2003; Helsper, 2021; Lythreatis et al., 2022) and they directly impact D&I in the workplace. Conversely, technologies can reduce inequities and generate new enabling mechanisms of inclusion with assistive technologies for example (Roulstone, 2016). The digital and physical worlds are deeply intertwined, and we must understand how the norms of abilities and disabilities evolve during the technological revolutions.

According to the social model of disability, abilities and disabilities are social constructs shaped by the environment. Ellis and Kent (2011) pointed out how the industrial revolution associated with mass production and the assembly line during the last century has structured new stereotypes and forms of exclusion. Mass production generated the notion of able-bodied normality, which favoured the oppressive discrimination of workers with physical disabilities. Machines were designed to be used by the greatest number of people with the least amount of adaptation, resulting in a standardisation of the physical characteristics of the workforce.

Whilst previous industrial revolutions generated more physical power and complemented human ingenuity, current digital transformation is generating a new form of mental power and control system through automated decision making procedures. Therefore, the current digital transformation presents a risk of standardisation of the mode of thinking. Analysing neurodiversity initiatives and digital transformation together is crucial and relevant given that they reconfigure the intelligence ecosystem in the workplace. This transformation relies on the historical evolution of perceptions, cognition, and decisions using digital technologies. Image, voice, and speech recognition technologies are directly related to the existing human sensory environment for collecting information. Augmented reality (AR) and virtual reality (VR) create a new sensory environment. Cognitive computing, deep learning, machine learning, and

AI assist organisations in standardising and automating new and old processes. The decision itself can be automated through smart contracts, which are self-executing digital contracts stored on blockchain technologies (Davidson et al., 2018). This new configuration of synergies between human and machine intelligence represents a critical juncture in D&I analysis.

2.2 | Algorithmic biases and discrimination

When analysing the relative performance of decision making of automated systems and humans, academic papers across various disciplines pointed out the necessity to develop non-biased, fair, and equitable algorithms, AI, and digital technologies. More than 50 years ago, after developing the natural language processing ELIZA to better understand interactions between technologies and humans, Weizenbaum (1976) argued that comparing automated decisions made by machines or algorithms to decisions made by humans was inappropriate because it removes ethical and moral judgment from choices. Leicht-Deobald et al. (2019) analysed new ethical challenges raised by algorithm-based HR decision making, arguing that it may crowd out the human integrity and trust embedded in human decisions. In HR, where decision making applies to people and impacts their working life, AI and automated decision making create new challenges (Cappelli et al., 2020; Strohmeier, 2022) in terms of D&I. If the performance of an algorithm is not related to fairness or equity, algorithmic biases may put vulnerable categories protected by law at a disadvantage.

Human, data, and socio-economic algorithmic biases (Institut Montaigne, 2020; Lattimore et al., 2020) reflect different forms of discrimination that have been extensively analysed in HRM (Berscheid & Walster, 1978; Tajfel, 1981) and discrimination theories in economics (Arrow, 1973; Becker, 1971). To understand algorithmic biases, let us successively consider:

(1) cognitive and human biases of workers encoded into algorithms (Cappelli et al., 2020; Crawford et al., 2019; Leong et al., 2019; Raub, 2018);
(2) statistical biases generated by data collected to train algorithms (Barocas & Selbst, 2016; Bertail et al., 2019; Cappelli et al., 2020; Köchling & Wehner, 2020; van den Heuvel & Bondarouk, 2017)
(3) socio-economic biases related to the context where algorithms are implemented (Lambrecht & Tucker, 2019).

Firstly, algorithms may embody human discriminatory behaviour because they are designed by humans (Leong et al., 2019; Raub, 2018). Cognitive, emotional, or affective biases are directly related to the lack of diversity in the IT industry, especially in the AI industry (Crawford et al., 2019; West et al., 2019). For example, in 2019, Black workers represented less than 4% of the workforce at Google, Facebook, and Microsoft. As argued in social categorisation theory (Tajfel, 1981) or the similarity/attraction paradigm (Berscheid & Walster, 1978), such homogeneity favours stereotyping and cognitive biases. How coders, developers, workers tagging or scoring images may embody themselves, and their stereotypes may strongly shape human-algorithm interactions (Lee, 2018). Bertail et al. (2019) identified several mechanisms that transfer human biases into algorithms: bandwagon bias (coders prefer popular models), illusory correlation bias (independent events are considered correlated), and anticipation or confirmation bias (coders favour their own view of a phenomenon). These cognitive biases strongly echo the taste-based discrimination theory formulated by Becker (1971) that argues that employers, employees, and consumers have discriminatory preferences that spread through the workplace, institutions, and markets. With digital transformation, taste for discrimination is encoded into algorithmic biases. Given that data scientists know little about the employment context (Cappelli et al., 2020) and the homogeneity of the IT workforce (Crawford et al., 2019), predictive algorithms that support HR processes can spread these biases and impact D&I.

Secondly, another important source of bias comes from the statistical biases and datasets used to train the algorithms. Inaccurate, unrepresentative, insufficient, or outdated data can generate algorithmic biases (Barocas & Selbst, 2016). Van den Heuvel and Bondarouk (2017) used the 'garbage in—garbage out' adage to underline that in

HR analytics, brilliant analyses using biased data produce little value. Köchling and Wehner (2020) demonstrated that these data biases are widespread in algorithmic decision making in HR recruitment and development. This issue is even more problematic for workers with disability, including neurodiverse workers who are incorrectly or inappropriately represented in the datasets (Whittaker et al., 2019). The historically poor representation of minorities in these datasets generates selection biases, missing variables, or censored data that generate biased outcomes that disadvantage minorities (Institut Montaigne, 2020). These statistical biases strongly echo the statistical discrimination theory formulated by Arrow (1973), which explains that the lack of information on some individuals, causes decision makers to discriminate statistically by inappropriately inferring the average of a group to individuals. For example, the lack of information on applicants' productivity and turnover causes employers to discriminate statistically. Typically, data collected on workers for recruitment purposes are always incomplete, as information about applicants who were not selected is typically omitted from the dataset used in the future, generating a selection bias. In HR decisions related to recruitment or evaluation, Cappelli et al. (2020) showed that selection biases that are not understood and controlled appropriately can generate a collider effect that identifies false correlations between variables and can cause algorithmic biases that will persist over time.

Thirdly, real-world context of implementation of algorithms can generate intentional and non-intentional biases. The search engine manipulation effect (Epstein & Robertson, 2015), which raises important ethical questions, is a good example of intentional bias coded to shift the preference of a target population online and influence their behaviour related to real-world decisions. Technologies are becoming a central feature of the new socio-political context that may structure D&I, as algorithms are used as a tool of powerful dominance to shift preferences and behaviours. Johnson and Stone (2019) contextualised eHRM in real-world systems to evaluate the expected benefits and unintended consequences of technologies to achieve HR goals in terms of attraction, motivation, retention of employees, and HR planning. Amongst the unintended consequences, the potential reinforcement of the digital divide and algorithmic biases are directly related to D&I. These contextual biases are often unintentional and relate to the complexity of the socioeconomic environment. For example, Lambrecht and Tucker (2019) demonstrated the complexity of socioeconomic bias by explaining why a recruitment ad for a STEM position was shown more frequently to men than to women. As the ad did not specify a gender target and other advertisers were paying more to reach women, the minimisation of costs and maximisation of exposure increased the cost of advertising to the female segment. Although the algorithm was not biased, the economic context in which it was implemented generated a non-intentional economic bias.

Finally, we stress why algorithmic biases create new loops of discrimination at the global level. As algorithms are inexpensive and easy to scale, they generate productivity gains that support their adoption and rapid diffusion (Eubanks, 2018; O'Neil, 2016). A small algorithmic bias can have substantial consequences in terms of discrimination if they are not fixed, given that it may rapidly spread across organisations. Moreover, the absence of accountability of an algorithm means that the coder is not responsible for the decisions made by his or her algorithm, opening the door to irresponsible decisions (Eurofound, 2022; Leicht-Deobald et al., 2019). In the case of tools that automate HR decisions, vulnerable categories of workers protected by antidiscrimination laws may be at risk. The growing academic literature on automated decision making in HR (Bondarouk & Fisher, 2020; Johnson & Stone, 2019; Meijerink et al., 2021; Strohmeier, 2022), which encompasses e-HRM, HR analytics, HRM algorithms, and HRM practices based on AI, demonstrates efficiency gains and new risks of these technologies. Efficiency gains are generated by optimising resources, routing, and scheduling the workforce (Cheng & Hackett, 2021). The use of descriptive, predictive, and prescriptive algorithms (Leicht-Deobald et al., 2019) in recruiting, selecting, or training to describe and predict job satisfaction or work-related attitudes, motivation, and employee turnover also represents a potential source of benefits to the implementation of algorithms to support decision making (Cheng & Hackett, 2021). These tangible benefits drive the rapid adoption of technologies, and algorithmic biases have been clearly identified as a new risk for D&I (Cappelli et al., 2020; Leicht-Deobald et al., 2019; Meijerink et al., 2021). Hence, trustworthiness, transparency, explainability, accountability, responsibility, justice, and fairness are becoming ethical principles in digital workplaces (Eurofound, 2022; Leicht-Deobald et al., 2019). Despite that these important ethical discussions are beyond the scope of our paper, our research on technology use in the context of neurodiversity initiatives contributes to understanding the properties of technologies that support inclusion.

2.3 | Coevolution of D&I with the technological environment

This multidisciplinary literature review demonstrates that physical and digital environments are coevolving and governed by analogous mechanisms in terms of discrimination. Algorithmic biases drive the replication of discriminatory mechanisms in virtual environments. Access barriers to technologies reinforce inequalities by widening the digital divide. This new technological construct of inequality echoes the social construct of disabilities examined by disability studies. However, the coevolution of D&I and digital transformation is not merely an unavoidable determinism that leads to an infinite replication of discriminatory behaviours and global inequalities. The digital transformation creates both disabling and enabling mechanisms. For instance, assistive technologies (Roulstone, 2016) can facilitate new forms of workplace inclusion. To enhance D&I, a better understanding of how the transformation of the technological environment can support new inclusion-enabling mechanisms is required.

Bias, stereotypes, norms of abilities, and disabilities are coevolving with a changing technological environment. In the current context of transformation of the intelligence ecosystem rooted in the rebalancing between human and machine intelligence, as presented in Section 2.1, how digital technologies can be used to favour and value the diversity of human minds that represents the tacit knowledge referred to in Polanyi's paradox mentioned in the introduction must be identified. In our view, tacit skills are intrinsically blended with each worker's singular identity and experience. The codification and transcription of new knowledge depend on how problems are searched, framed, interpreted, and solved. Differences in perception, cognition, and learning of neurodiverse employees may become a cornerstone of D&I comprehension. The remainder of this paper examines how technologies are implemented within the context of D&I initiatives that target neurodiversity. It will aid in identifying the properties of technologies that support D&I enablement mechanisms and evaluating them critically.

3 | ROLE OF TECHNOLOGIES FOR THE INCLUSIVENESS OF HR PRACTICES TARGETING NEURODIVERSITY

This section analyses what neurodiversity brings to the analysis of D&I and presents the results of qualitative research that studies the digital dimension of neurodiversity initiatives.

3.1 | What does neurodiversity bring to the analysis of inclusion?

Firstly, the neurodiversity paradigm clearly defines differences as deviations from a (medical) norm for neurominorities. For Macdonald (2019), the outright rejection of the concept of disability and impairment and celebration of difference clearly distinguishes the neurodiversity paradigm from the psycho-social model and socio-cultural model of dyslexia. A deviation from a norm generates a social distance between individuals. As cognitive, emotional, social, cultural, or physical distances between individuals are heterogeneous, contextual, and dynamic, neurodiversity represents a form of cumulative distance between individuals, which is a continuum and cannot be simplified to static categories. Diversity in the workplace requires questioning the applicability of norms used to categorise workers and how they are expected to fit into a homogenous model.

Secondly, the neurodiversity paradigm overcomes existing dichotomies between surface- and deep-level diversity, or visible and invisible diversity, which represent a binary construct in the D&I ontology (Nkomo et al., 2019). Focusing on differences in perception, cognition, and interaction, which are the core abilities of all workers, the neurodiversity paradigm brings 'deep differences' between individuals to the 'surface'. In the 19th century, for instance, dyslexia was referred to as 'word blindness', and various neurocognitive functions were associated with it. For people who are blind or deaf, workers with dyslexia perceive reality differently. Communication and interaction may also be affected by perception, as demonstrated by cross-cultural variations in body language. An important variation exists in how people understand, interpret, and 'use' body language in different contexts, such as autistic workers. Keeping in mind that differences represent a distance from the norm, successfully incorporating neurodiverse individuals can benefit workers whose perceptions, cognitions, or interactions are distinct, such as culturally and linguistically diverse individuals or people with disabilities.

Thirdly, and more importantly, the analysis of neurodiversity initiatives demonstrates that mental well-being management is a core element of D&I initiatives due to the strong intersectionality between anxiety, depression, and ADHD or Autism Spectrum Disorders (ASD) (Uljarević et al., 2020). The intersectionality between mental wellbeing and D&I is a universal question that has been overlooked in the diversity literature, and the results obtained for a neurodiverse population may be useful to other vulnerable employees.

3.2 | Research method: A qualitative analysis of neurodiversity initiatives

Neurodiversity initiatives are managerial practices implemented to favour the employment of neurodiverse workers. The creation of such an inclusive environment is often presented as an accommodation. Austin and Pisano (2017) pointed out that neurodiversity initiatives require non-interview methods of recruitment, assessment, training, managing, and teaming with experts of neurodiversity before scaling and mainstreaming the programme. However, this managerial literature does not consider the role technology plays in neurodiversity design. One exception is Walkowiak (2021), who argued that productivity gains can be generated at the individual, organisational, and macroeconomic levels by combining technologies and organisational practices that target the employment of autistic workers. Using the same primary data, our analysis focuses on the organisational level and does not specifically concentrate on autistic workers. Moreover, rather than focusing on productivity gains associated with the implementation of technologies, the technological properties that favour D&I in neurodiversity management are analysed.

Following Walkowiak (2021), this qualitative research relies on a phenomenological approach in which two criteria of participant selection were used in a purposive sampling strategy: leadership or expertise in neurodiversity initiatives and good knowledge of the IT sector. The phenomenological approach generally relies on a sample of 5–30 participants. Sixteen participants were interviewed in 2018 and 2019 between 55 min and 2 h to obtain the saturation level. Participants were initially selected due to their leadership role in neurodiversity initiatives that we identified when they were attending, organising, or presenting during conferences or forums on the employment of neurodiverse workers in the USA and Australia. Once identified, the expertise of the participants was verified by looking at their involvement level in the neurodiversity initiative on their company's website and on LinkedIn. Participants were engaged in neurodiversity initiatives of various maturities and scales. The high level of expertise and intensity of the contact provided rich and complex primary data. Participants shared their lived experiences and opinions on neurodiversity initiatives in a reflective manner. Comparing and contrasting these experiences increased our ability to understand their lived realities. In addition to their strong professional expertise and leadership role in neurodiversity initiatives, three participants spontaneously informed us that some close family members had neurodiverse conditions, and one participant mentioned being on the autism spectrum. The composition of the sample is provided in Table 1. Participants were located in Australia (eight participants), the USA (seven participants), and Canada (one participant) and working in firms from different industries. In our sample, 37.5% of the participants were female.

TABLE 1 Sample composition.

Location		
Australia	8	50%
North America	8	50%
Gender		
Male	10	62.5%
Female	6	37.5%
Industry		
IT	6	37.5%
Bank/finance	2	12.5%
Accounting	1	6.25%
Social enterprise	2	12.5%
Charity	1	6.25%
Disability service	1	6.25%
Academia	2	12.5%
Total	16	100%

After sending the questionnaire, semi-structured interviews were conducted face-to-face or via phone or Skype, depending on the location of the participants. Participants were probed on the organisational design of neurodiversity, for which the following questions were asked:

> For you, what are the key features or the 'best practices' of an organisational design that favours the employment and the development of a neurodiverse workforce? What is the role of technologies (if any) to favour an organisational design that promotes neurodiversity? Can you give examples? Do you identify any specific risks with digital technologies? Do you think that digital technologies can improve human resource management practices targeting neurodiversity?

Table 2 summarises the coding of the materials and shows the number of participants who discussed each theme. Following the recommendations of Moustakas (1994), the coding of the material started with two broad code types (digital technologies and HR practices), and subcodes were identified from the data. The code structure was revised and enriched using open coding methods to identify new themes that emerged across interviews (Corbin & Strauss, 2015). Various technologies, such as assistive technologies, virtual reality, and biometric technologies that interact with neurodiversity management, were identified. For example, physical and mental well-being is a category that emerged from the data for HR practices. Table 2 highlights the properties of technologies that support the inclusiveness of HR and shows the areas of HR practices that were presented by participants.

3.3 | Results

3.3.1 | Technologies neutralise biases in the evaluation of performance

Technologies can neutralise the subjectivity of the interview process by increasing the rationality of the performance evaluation. Participants clearly identified the interview as a barrier to inclusion given that it is a process in which interviewers may activate stereotypes. Recruitment procedures and performance evaluations that rely on interviews can be supported by technology to become more objective.

TABLE 2 Properties of technologies and HR practices.

Themes	Subcodes
Properties of technologies	
Technologies to neutralise biases (15 participants—94%)	Technologies to evaluate problem solving capacity on the spot in IT roles: Programming languages/robotics/games/coding
	Technologies to monitor performance: Distributed support/dashboard/digital feedback/remote-digital monitoring/remote supervision
Screening and matching technologies (10 participants—63%)	Professional platforms/matching platforms/biometric platforms/digital behavioural data
Technologies for awareness and digital marketing (16 participants—100%)	Social media platforms/social networks/viral
Technological accommodation for mental and physical well-being (13 participants—81%)	Assistive technologies/technologies for flexibilisation of the ergonomy in the workplace (headset, light control, colour control)/virtual reality for mental health/emotion recognition technologies
Diversification of modes of interactions and cognition (16 participants—100%)	Communication technologies/synchronous-asynchronous interactions supported by technologies/verbal-non-verbal communication supported by technologies/digitisation of content/virtual reality for learning/social media
HR practices	
Physical and mental environment (15 participants—94%)	Physical: Open space/light/colour/noise/stimulation area
	Mental: Anxiety/stress/comorbidities/disability/planning difficulty
Recruitment (16 participants—100%)	Sourcing/Matching/Screening/Assessing/Sorting/Candidates/CV
Training and awareness (15 participants—94%)	Training of neurodiverse workers/training of co-workers/training of managers/awareness/training material
Support and supervision (13 participants—81%)	Support/supervision/performance management/evaluation/coaching/buddy/feedback

Technologies help to separate two elements in the evaluation of performance: (1) the assessment of the performance of individuals in completing a task, and (2) the quality of an interview which comprises communicating a narrative about individual performance. The first element is a direct measure of performance. The second element may be biased by the social construct of the workplace performance narrative. Participants explained that many elements can bias the narrative of performance, such as body language, facial expression or voice tone, and subjective impressions that it generates. Given that wide differences exist in the communication styles of individuals, these subjective impressions generate biases in the recruitment process that should be neutralised. They demonstrate the importance of relying only on a direct measure of the capacity to complete a task rather than a description of this performance during an interview, as summarised by the following quote:

> The more rational the recruitment process could be, the better it would be for autistic people because recruitment rules are often about, 'Excite me', and is that important? Isn't it; 'Show me your ability to do this and this and this work. This is what matters.' (Participant from social enterprise, USA)

Technologies provide new tools for assigning tasks to candidates, assessing their performance, and monitoring the evaluation of their skills without directly interacting with them. This double role of technology in terms of the assessment of performance and neutralisation of stereotypes is well described in this example:

> There are applications that I can write a technical set of questions to test somebody's ability in SQL or in Java and to answer these questions and these problems that way, through technology. The importance of this is by having the information passed technologically, I don't hear a voice and I don't see a face. (…) But what I will have through that technological assessment is I'll know how deep their understanding of Java or SQL is. I think that's important to create a blind test initially because it removes the human biases that so many of us have. (Participant from the IT industry, USA)

The importance of neutralising the interview component from the performance evaluation was also identified as relevant for performance evaluation. The pros of the digitisation of supervision for performance evaluation are illustrated in the following quote:

> When it comes to performance and reward, again that literalness of the performance being in front of you on-screen, agreed and measured, and being able to say the progress in an automated dashboard, I think again it's much better than coming into a room and hearing the sort of conversation that says 'I'm happy with you, but there's a few things you might want to change'. (Participant from bank and finance, Australia)

3.3.2 | Digital matching technologies for an inclusive screening of applicants

Matching platforms are efficient tools for developing a digital recruitment strategy. The participants pointed out two benefits of professional matching platforms: cost efficiency and audience scope. These two properties contribute to reducing search and matching costs for employers and candidates. As neurodiversity initiatives focus on a specific segment of the labour market, the pool of vacant jobs and applicants represent a smaller proportion of potential matches. In the following quotation, matching platforms are presented as a key element of a digital recruitment strategy to favour neurodiversity, suggesting that better targeting of neurodiverse workers through these platforms is possible.

> The biggest impact technology can have in the organisational design of neurodiversity is connecting employers with candidates in a more efficient way. If I'm a candidate on the autism spectrum, no matter my background, I'm looking for a job. It's very hard to find inclusive employers looking to hire candidates on the autism spectrum. If technology like LinkedIn or other platforms, could better identify and match candidates with employers, that would help impact unemployment rate. (Participant from bank and finance, USA).

Some participants explained how to improve the matching process using additional matching criteria with AI and neuroscience applications that measure cognitive traits. Providing additional and alternative measures of performance to the CV allows the sorting, screening, and matching of candidates on the basis of the new criteria:

> So, if someone applying for the job displays a good fit with the 10 to 15 traits that signify you have a good person in that role, then they'll get through the first filter. That's opposed to some other techniques that are currently used, like doing a word search on a CV, or spending five seconds looking to save in deciding whether someone's in or out. It's a much better approach to doing that first filter. You

> wouldn't appoint someone just on that, but it's that first filter. Instead of hiring someone who might be good at writing a CV and putting all the right keywords in, you may be hiring someone who has the traits that actually who's successful in a job. (Participant from social enterprise, Australia)

3.3.3 | Platform for storytelling in the workplace and digital marketing of diversity

Participants underlined the importance of social media platforms, such as Instagram, Facebook, Twitter, and YouTube, in improving neurodiversity awareness. Several social media properties have been identified. They increase audiences within and outside the firm's boundaries. Technologies enable the oral tradition of knowledge transmission through storytelling to occur in the workplace, as videos on neurodiversity uploaded to social networks feature the personal stories of neurodiverse employees. Combined with more traditional media, these are key elements in increasing awareness of the social model of disability and expanding how diversity and disability are seen in their full complexity. Although the role of social media in awareness and storytelling is well known in society, it also represents a strategic component of the development of inclusion practices in the workplace by promoting the CSR initiatives of businesses. Participants noted that viral marketing of these initiatives on social media is a cost-effective way to raise awareness of neurodiversity initiatives, facilitate their implementation, and improve their efficacy.

> The role of awareness is huge. (…) Awareness feeds us the people who want to help the mentors, buddies, coaches. It feeds us hiring managers who need to fill jobs. (…) It also feeds us referrals. I get a referral both internally and externally of people who we might be able to hire. (…) If you look at LinkedIn, YouTube, Facebook, you'll see that much like many companies that are starting to advertise using social media because it's cheaper than TV and radio and it's got the contagious effect where people share it, like it, pass it along and it fills up news feeds. (Participant Bank and Finance, USA)

3.3.4 | Technologies to support mental and physical well-being in the workplace

Participants also mentioned some specific difficulties associated with the employment of neurodiverse workers and in the following quote on the employment of autistic workers:

> We need to understand that autistic people are different for a reason, and as much as we can celebrate the gifts and talents of those people, 80% of them also come with comorbidity. (…) You need to support some of the challenging things that they will face. It is relationship-building and communication, but beyond that, it is severe anxiety, it could be other mental issues, it could even be learning delays, all of these other things that typically come with autism. (Participant from the banking industry, Australia)

Eleven participants mentioned that mental well-being or mental health policy are required for the success and sustainability of these initiatives and the management of stress or anxiety in the workplace. Three participants discussed the potential role of emotion recognition technologies in monitoring, managing, and reducing anxiety. Four participants shared their experience of using virtual reality (VR) to prepare workers or managers to manage stress or potentially uncomfortable situations. VR provides new immersive environments that can help develop skills to cope with stress or difficulties, as illustrated in this quote:

> If you are not sure whether this person is going to be able to manage an exposure to a situation that might be anxiety provoking or confronting, or challenging, with the use of technology, particularly

> virtual reality training, you can immerse somebody in an environment that's safe for them. (Participant from academia, Australia)

Generally, as pointed out in the literature on disability studies, assistive technologies offer technological accommodations to favour inclusion. For example, text-to-read software, dictaphones, secretarial support, electronic organisers, and audiobooks represent assistive technologies that favour the inclusion of workers with dyslexia (Macdonald & Cosgrove, 2019). Participants demonstrated that technologies can provide a flexible ergonomic workspace that can be customised on the basis of individual needs. They showed that simple technologies, such as headsets or different light colours, can improve the concentration and productivity of neurodiverse workers. The following quote illustrates the benefits of using digital assistants:

> There are a lot of benefits in technologies of AI, like Siri and personal assistance like Amazon Echo. There are many benefits, I would say for people with disabilities, in general, whether you are blind or whether you have autism. There are advantages of being able to get concise, easy answers, anytime in a consistent, repetitive manner. I think there are some advantages of what I call the personal assistants. (Participant from IT industry, USA)

3.3.5 | Technologies diversify the modes of communication and learning

Finally, digital technologies provide tools for diversifying modes of interaction and learning in the workplace. In general, the role of technology is well understood for the general population. Our findings highlight the substantial benefits for neurodiverse workers, for whom these inherent properties of technologies provide a necessary accommodation for varying perceptions, communication styles, and learning styles. For example, technologies enable face-to-face, online, oral, or written communication in real time, as well as asynchronous communication. Diversification of modes of communication or learning provides more flexibility. Inclusion is contingent upon the diversification of modes of communication and learning for neurodiverse employees. Participants emphasised that these technological properties favour the inclusiveness of HR at various levels in the sourcing of candidates during recruitment, training, and supervision.

During the recruitment process, at the sourcing stage, technologies offer different contact channels to source neurodiverse candidates. Digital technologies support a more universal contact phase and flexible interaction modes.

> For the sourcing part we use technology all the time to be able to interact with the candidates. Some people prefer the e-mail communication versus verbal communication. Some people prefer to do Skype so that we can talk to them. But they prefer not to come on site. So, yes, we utilize technology most definitely in that. (Participant from the IT industry, USA)

Training is an important component of neurodiversity initiatives, and technologies contribute to the inclusiveness of training by accommodating different learning styles and preferences. The digitisation of training materials offers flexibility in delivery modes, allowing for real-time or asynchronous training. Digitisation reduces the cost of training, expands the potential audience, and offers an effective means of raising awareness about neurodiversity initiatives.

To favour inclusive supervision, neurodiversity management generally involves job coaching during a period. In this ecosystem, buddies and mentors are trusted supervisors. Digital technologies can reduce the cost of supervision and facilitate it by providing a remote and distributed support network for the workplace and home environment.

One participant provided examples of applications or automated dashboards that can be used in the workplace to facilitate supervision:

> Buddies and mentors are spending a lot of time on the routine things. 'Have you done this? Have you done that?' Or, even doing checklists and giving checklists. (…) With a remote support, you have a more distributed part of people who've got this to support. (Participant from a social enterprise, Australia)

4 | DISCUSSION

We argue at the beginning of this paper that the transformation of the intelligence ecosystem in the workplace represents a critical juncture for D&I management given that digital technologies diversify the options and choices for reconfiguring workplaces. No technological determinism exists in D&I, but rather various possible trajectories that relate to the newly identified inclusion and exclusion mechanisms identified in this paper. This study demonstrated that digital technologies replicate discriminatory behaviours via algorithmic biases and shape new inclusion mechanisms, as evidenced by their role in supporting neurodiversity initiatives. This section critically analyses three fundamental aspects of D&I coevolving with technologies: performance evaluation, new forms of dominance, and mental well-being.

4.1 | The changing narrative of performance

CVs and interviews are two major managerial tools for evaluating workers. They provide proxies for performance that may be biased (Cappelli et al., 2020) by translating indicators of performance into words. Our results show that, for neurodiverse workers, these biases may be stronger compared with the rest of the population due to different forms of interaction and communication amongst neurodiverse workers. The translation of performance into words (i.e. the capacity to elaborate on a narrative of performance) is a source of bias clearly identified for the neurodiverse population. For this reason, neurodiversity recruitment practices rely on non-interview-based assessment and directly observe performance on the spot, looking at individuals completing a task rather than asking them to explain (with words) how they would complete a task. With digital technologies, the elaboration of performance narratives is evolving in different directions, raising new issues for D&I. To simplify, let us consider two categories of evaluation tools: tools based on words (CV and interviews) and tools based on alternative metrics (e.g. cognitive scores).

AI-based tools for screening resumes (Derous & Ryan, 2019) and pre-recorded video interviews (Mirowska & Mesnet, 2021) are rapidly developing because they automate the pre-screening process, save recruiter time, and process a large number of applications. They use CV and pre-recorded answers to interview questions, which may be considered as 'traditional' tools or technologies to generate a synthetic narrative of performance, as an input for machine learning or algorithms. More precisely, CV translates educational and professional achievements into keywords that are inputs for algorithms that screen applications. Thus, how existing biases in a CV can be scaled through technologies must be understood. In 2015, Amazon ended its AI-based candidate evaluation tool used to assist HR services because it encoded discriminatory behaviours against women in the ranking of applicants based on keywords. This AI tool provided a useful snapshot to understand patterns of discriminatory behaviours in the sorting, selection, and ranking of CVs by AI. AI-based tools that use CV as inputs display existing discriminatory behaviours into algorithmic bias because they rely initially on a biased narrative. Although AI represents a powerful tool to reflect and detect discriminatory behaviours through keywords, the technology will not fix the bias. More research is needed to evaluate verbal content and linguistic patterns of discrimination. Similarly, AI screens verbal content, body language, non-verbal behaviours in pre-recorded interviews. Once again, algorithmic bias may be very important and may exclude some categories of workers. How these technologies deal with workers from different cultural backgrounds, different accents, or different body language, as for autistic workers, must be further explored. Interestingly, Mirowska and Mesnet (2021) showed that in recruitments relying on AI-based screening of videos, applicants reported that AI is more objective and less biased in evaluating applications even if they had a strong preference for human evaluation in the selection process.

Our results also suggest new options offered by technologies to proxy performance that suits well non-interview-based recruitment practices implemented for neurodiverse workers. For example, new metrics of cognitive performance, concentration, or personality traits of applicants when playing a performative game can be easily collected through technologies. Technologies offer new possibilities for directly assessing the performance of individuals without elaborating a narrative of performance. This raises new and important questions for the certification of performance. Who certifies the performance of who, and for what purpose? More generally, more research is needed to identify how these new performance metrics complement or substitute more traditional measures of performance and their impact on D&I. In both cases, proxies of performance through words or other metrics generate a bias, but the nature of this bias may differ by metric.

4.2 | New forms of dominance

This study argues that the coevolution between D&I and digital transformation is driven by new inclusion and exclusion mechanisms. The transformation of the forms of dominance is underlying inclusion and exclusion mechanisms mediated by technologies. Interestingly, algorithmic biases, self-advocacy through technologies, and privacy issues were not mentioned by the participants in this research. In this section, we critically discuss these topics to highlight the dual role of technologies in D&I.

By contextualising the use of technologies within neurodiversity initiatives, the empirical results (presented in Section 2) point out the properties of technologies that support enabling mechanisms for D&I. This inclusive role of technologies for HR contrasts with the replications of discriminatory behaviours embodied in algorithmic bias, automated decision systems (presented in Section 2.2), and the deepening of the digital divide (presented in Section 2.1) that were discussed at the beginning of the paper. It is worth noting that none of the participants leading the neurodiversity initiatives mentioned using automated systems of decisions. In neurodiversity initiatives, technologies do not replace human decisions or actions, but support or complement decisions made by leaders, managers, coaches, supervisors, and co-workers with the purpose of inclusion of neurodiverse workers. Neurodiversity design is based on a new human ecosystem, where technology is mainly used as a supporting tool for an unbiased human decision infrastructure.

The role of social media in neurodiversity awareness has been presented as an important element of these initiatives. Hosain (2021) and Johnson et al. (2022) provided a detailed review of the literature on the role of social media and social networking sites in HRM practices, such as talent search, recruitment, selection, employer branding, legal and ethical concerns using social media for hiring decisions, and the growing storage of information on employees. Although reviewing this rich literature in detail is beyond the scope of this paper, the dual role of social media in neurodiversity initiatives must be considered. In the case of neurodiversity initiatives, employers use social media to promote awareness of their initiatives and potentially improve their reputation. In the HR literature, the role of social media in shaping applicants' perceptions and attracting talent clearly demonstrates the central role of technologies in signalling employers' reputation (Carpentier et al., 2019). The specificity of neurodiversity initiatives is that employers become self-advocates of neurodiversity online. Interestingly, the role of technologies in self-advocacy and self-determination within the workplace as part of D&I was not mentioned during our interviews. While it may be due to the lack of maturity of these initiatives or the composition of our sample, it may also indicate the dual role of social media in HR, which drives both new inclusion and exclusion mechanisms. In disability studies, Ellis and Kent (2017) argued that social media can be empowering for self-determination and self-advocacy, favour awareness about differences, and drive innovation for D&I in the workplace. Meanwhile, in the HR literature, Black et al. (2015) argued that using social media websites in hiring processes may generate stigmatisation of workers with disabilities or other protected categories of workers and represent an invasion of their privacy. Once again, there exists no deterministic role for social media in D&I, and both inclusion and exclusion mechanisms are at stake. When individual stories are posted on social media, the empowering or disempowering role of technologies can be analysed by answering simple questions: who is posting the stories, for what purposes, and for what benefits? The commodification of D&I in general, or neurodiversity more specifically, presents potentially a new form of dominance and a new risk for self-advocates of neurodiversity (Singer, 2020). More research is required on the potential commodification of D&I, especially when employers post individual stories about their employees on social media.

The collection and storage of personal information allowed by technologies also raise privacy concerns that should be analysed through the D&I perspective. None of the participants involved in this research mentioned any problem related to privacy issues. Privacy represents an ethical, legal, economic, and managerial challenge (Black et al., 2015; Cappelli et al., 2020; Leicht-Deobald et al., 2019; Stone & Stone, 1990; Tucker, 2019) that should be urgently addressed. Data persistence, repurposing, and spillovers (Tucker, 2019) can generate unexpected forms of inequalities and exclusion that are not sufficiently identified, understood, and analysed. How privacy issues will impact different categories of workers, inequalities, and D&I over time remains an open question for researchers.

Algorithmic biases, legitimacy of online self-advocacy by employers, and privacy challenges show the complexity of the coevolution between technological and social change. The identity, incentives, and purpose of designers and leaders of change, which may be technological or social, are essential in shaping new forms of inclusion, empowerment, or dominance in the workplace. Thus, who is designing the change, for what purpose, and for what benefits must be analysed and understood.

4.3 | A digital ecosystem for mental well-being

The intersectionality of mental well-being and health with other vulnerabilities is a universal dimension of D&I that requires more attention. The role of D&I of the workforce in the mental health and well-being of workers, the intersectionality of mental health, and discrimination represents an area of research that should be further developed. Recent data from the US Census Bureau show nearly a tripling of persons experiencing anxiety and depression during the COVID-19 pandemic in the USA, with Black Americans shouldering the heaviest burden (American Psychiatric Association Foundation, 2020). Using matching models and Oaxaca-Blinder decomposition methods, Platt et al. (2016) showed that higher probabilities of anxiety and depression for women are significantly caused by gender wage gap and discrimination in the workplace. In Australia, the Productivity Commission (2020) pointed out that in workplaces with high job demands and low employee controls, a gap between effort and reward and a low level of organisational fairness create psychosocial risks that are detrimental to workers' well-being. The cost to employers can be measured in terms of increased absenteeism, compensation claims, and reduced productivity. Our results show that the role of technologies in mental well-being can be direct and indirect.

Firstly, a new market for technological solutions for mental health is growing. It provides platforms and tools that are directly related to the emotional, psychological, and social well-being of individuals, such as tools for emotion recognition technologies used to monitor stress and anxiety. Emotional AI is defined as a technology that uses affective computing and AI tools to recognise, learn about, and interact with human emotional life (McStay, 2020). Some participants in our research recommended that neurodiverse workers use wearables in the workplace, such as smart watches or glasses, to monitor stress on a voluntary basis. This result highlights the positive role of wearables that integrate emotion recognition technologies to support mental health to improve well-being. Wearables are defined as technologies designed to be worn on the body, including electronics, sensors, and software, which provide new ways to collect information about employees (Billinghurst & Starner, 1999), including their health. Johnson and Stone (2019) underlined that they represent efficient technologies to maintain the physical health of employees and facilitate communication about health in the workplace. Eurofound (2022) argued that tracking sensors can improve worker safety by detecting hazardous conditions in physical environments and triggering automated alerts. Our results extend these benefits to mental health, as these technologies can help monitor anxiety. However, the use of wearable or emotion-recognition technologies is also extremely controversial given that these technologies can be used as new tools for surveillance and authoritarianism (Doberstein et al., 2022; Kellogg et al., 2020) and may represent new forms of dominance. Moreover, their use in the workplace raises important privacy and data protection issues (Doberstein et al., 2022; Eurofound, 2022; McStay, 2020) as presented in Section 4.2.

Secondly, technologies can indirectly support mental health by improving the efficiency of HR practices that favour well-being. For training practices, our results identified an important emerging trend in the use of virtual reality (VR) to support mental health in the workplace. Let us define VR and augmented reality (AR), which are often analysed together. VR defines the technologies of immersion of individuals in a three-dimensional space where they can view, perceive, move, and interact with objects (Johnson & Stone, 2019). VR is a computer-generated scenario that simulates real-world experiences, whereas AR combines real-world experiences with computer-generated content (Eurofound, 2022). Johnson and Stone (2019) identified several potential positive impacts of VR on HRM, such as the immersion of candidates for a job in their working environment or improvement in training and learning. Eurofound (2019) provided an in-depth discussion and analysis of the development of VR in terms of employment, skills, working conditions, work organisation, and productivity, and presents multiple examples in the service sector. Both literature reviews (Eurofound, 2019; Johnson & Stone, 2019) highlighted that a VR training environment can contribute to improving worker safety by eliminating potentially harmful or risky environments. For example, Williams-Bell et al. (2015) demonstrated that VR is a safe and cost-effective technology for firefighter training.

In the case of the neurodiversity initiatives analysed in this paper, participants pointed out that VR is used for training to help workers cope with situations that generate anxiety and favour their inclusion. Results from psychology and psychiatry studies confirm the efficiency of such an approach. In a systematic review of 285 academic studies that analysed the impact of VR on mental health, Freeman et al. (2017) pointed out that VR exposure is highly efficient in reducing anxiety disorders. Moreover, VR changes the nature of training because it transforms teaching content into a meaningful experience. VR creates an emotional experience that promotes deep learning and provides a safe immersive environment that supports a strong concentration on the learning experience. As noted by PricewaterhouseCoopers, VR redefines soft skills training on many dimensions (PricewaterhouseCoopers, 2020), including an improvement in confidence in discussing and acting on issues of D&I after VR training. Moreover, the COVID-19 pandemic generated favourable conditions for the adoption of VR, since the technology complements physical distancing or working from home configurations well, in a context where the price of VR is dramatically falling, making it more affordable.

In summary, the role of emotion recognition technologies and VR in supporting mental well-being represents a promising research avenue for D&I programmes. However, the potential benefits and risks should be evaluated. Ethical considerations regarding the nature of data generated and collected through these technologies also raise new ethical challenges that should be scrutinised (Doberstein et al., 2022; Eurofound, 2022; McStay, 2020).

4.4 | Limitations of this research

This study holds limitations associated with the methodology used. Our biases on neurodiversity may have been transferred to this research. The low representation of neurodiverse leaders in our sample may also have biased the data collected. As for any qualitative research, our results are not directly generalisable to other groups but may be used to advance other research on diversity. For example, other co-occurring conditions sometimes associated with neurodiversity, such as intellectual disability and visual or hearing impairment (Do et al., 2017), were not analysed. Further research on the links between neurodiversity initiatives and digital transformation may identify different supplementary meanings.

5 | CONCLUSION

The current digital transformation offers new opportunities and risks for D&I. Choices made when redesigning the intelligence ecosystem in the workplace may produce different trajectories of inclusion or exclusion, depending on how technologies are developed and implemented. Our study provides a multidisciplinary perspective to understand this critical period of transformation. New possibilities are opened by technologies for a more efficient and fairer evaluation of performance to improve mental well-being at work and neutralise stereotypes and forms of dominance governing organisational processes. New risks are also emerging with algorithmic bias in decision making, the commodification of D&I through social media, or numerous privacy concerns raised by the implementation of technologies in the workplace. The standardisation of thinking that results from the constant screening of information through digital technologies is also a threat that should be further investigated.

This study jointly analysed neurodiversity initiatives in the context of digital transformation to advance the questions of D&I. Neurodiversity initiatives demonstrated the role of interviews in the activation of stereotypes and the importance of mental health in the workplace. We identified various properties of technologies (see Table 2) to improve the efficiency of neurodiversity initiatives and more generally favour the inclusiveness of HR practices in the recruitment, training and awareness, supervision and support, and physical and mental environments. Within neurodiversity initiatives, the properties that we identified relate to the neutralisation biases generated by social interactions during interviews, diversification of modes of cognition and interaction, support for physical and mental well-being, and improvement of awareness about neurodiversity. The large variety of technologies mentioned in this research demonstrates that no single set of technologies exists to favour D&I, as there is no technological determinism in the inevitable replication of inequalities through algorithmic biases.

In terms of practical implications, this research recommends that neurodiversity initiatives be systematically integrated into D&I policies. Specific attention should be given to the activation of stereotypes during social interactions, especially during recruitment and performance interviews. This research suggests different technologies that can be used to neutralise these biases and to support human decision making. Mental health and well-being management should be systematically integrated into D&I policies, in association with the implementation of assistive technologies. Wearable and VR technologies may also support mental health, if implemented with respect to privacy. Finally, privacy policies associated with the implementation of technologies should be systematically addressed through the lens of D&I.

ACKNOWLEDGEMENTS

I would like to thank Simon Bury, Cheryl Dissanayake, Darren Hedley, Jennifer Spoor for their comments, advice and support for this research. I am very grateful to anonymous participants who accepted to be interviewed for this research. I am grateful to participants of the OTARC seminar at La Trobe University, EFM seminar at RMIT, seminar on Transformative Innovation at Swinburne University, and Erudite seminar at University Paris 12, for their comments and suggestions. All opinions or errors are mine.

Open access publishing facilitated by La Trobe University, as part of the Wiley - La Trobe University agreement via the Council of Australian University Librarians.

DATA AVAILABILITY STATEMENT

Research data are not shared due to due to privacy or ethical restrictions.

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How to cite this article: Walkowiak, E. (2024). Digitalization and inclusiveness of HRM practices: The example of neurodiversity initiatives. *Human Resource Management Journal*, *34*(3), 578–598. https://doi.org/10.1111/1748-8583.12499