

Chapter 2. Previous Research

In the last ten years, there has been a significant increase in scholarly interest in AI's use in HRM, which is attributable to the development of technology and the growing experimentation of organizations in using algorithms to make decisions. Many studies (Tambe et al., 2019; Stone et al., 2015; Marler & Boudreau, 2017) have shown that most of the reasons behind the adoption of AI in HR are the organisation's desire for faster decision making, consistency and objectivity. The change that is relevant to performance evaluation is to replace the annual assessment with the subjectivity of the manager's judgment and provide system-generated performance data from digital work platforms to visually present performance continuously.

This phenomenon is described by Kellogg et al. (2020) as platform-style continuous monitoring, where the performance of employees is assessed mostly based on their work output in the form of digital productions and artifacts, instead of separate, periodic evaluations in meetings. In operational terms, this involves information obtained from documents, chat, email, participation in meetings and collaboration tools, that are converted into measurable signals that are integrated into the descriptions and ratings that can then impact employee results (Chen et al., 2021). This ongoing data collection and analysis is a radical shift away from the episodic evaluation model and adds time to performance assessment.

AI's potential within HR is also largely framed in terms of increased efficiency and standardization, consistent with the findings of previous studies. AI implementation is expected to bring benefits like streamlined workflows, increased consistency and better decision-making processes, which organizations look forward to (Tambe et al., 2017). Algorithmic objectivity, especially, has been appealing in situations where managerial bias or manageriality have been recognized as shortcomings of traditional approaches for measuring performance. But, the assumptions have

been problematised by scholars increasingly. The efficiency story is a good one, but it often hides the messy sociotechnical process unfolding as algorithms weave their way into existing organizational practices. Furthermore, evaluation with AI is perceived as objective, which questions how it is constructed and how the evaluation criteria are defined, as well as how the performance indicators are selected as value-laden organizational decisions.

2.2 How AI affects performance conceptions

In addition to studying motivations for adoption, existing studies critically analyse the impact of using AI on the substance of the evaluation process itself. The "benefits" of AI deployment have been observed to be unequally distributed among the various actors, and what is deemed as a successful performance varies. AI systems for work assessment actively intervene in what is seen, measured, and deemed valuable by choosing what actions, patterns, and behaviors to record and what to ignore on a systematic basis. In this regard, AI is not only quickening the pace of evaluation but can also transform the concept of evaluation in its very nature (Kellogg et al., 2020).

This is consistent with the scholarship of continuous and data-driven performance management. Real-time feedback, predictive analytics, and machine learning tools enable a shift away from standard evaluation practices, which focuses on periodic review to the proactive evaluation approach, and from static to dynamic evaluation (Adawiyah, 2024; Nyathi, 2023). This is a temporal and methodological change that has major impact on employee experience, management and HR professionals.

Agung et al. (2024) point to some issues of fairness, transparency and accountability that have appeared in previous studies. Adopting AI for HR selection might present difficulties in explaining the process and methodology behind the recommendation or score (Ying et al., 2025). This opacity

is especially serious, if employees challenge the evaluation results or managers want to know the basis for a decision. In such settings, HR professionals might be asked to back up findings that are partially based on data produced by the systems, and may not have a full understanding of the system logic or algorithmic processing (Nyathi, 2023). This puts HR professionals in a conundrum: they're expected to have a deep understanding of and control over the decision they're responsible for, yet they often don't.

The findings in this study indicate that AI can impose a new set of paradoxes of objectivity and partial explainability. In the era of AI-generated content, accountability for this in an evaluative process is essential for HR. Agung et al. (2024), Nyathi (2023), and Ying et al. (2025) identified issues such as inequitable outcomes, ambiguous processes, and lack of trust as still prevalent and pertinent problems in the context of AI assessments. A key space that needs to continue to be explored is the conflict between the seemingly more objective rationales of algorithms and the opacity and potential biases of such systems.

Moreover, researchers have focused on the performative aspects of the performance indicators. If certain behaviors are observed in AI systems as evidence of success, they also leave out other behaviors for consideration, which could then alter employee behavior towards measurable activities, and make less measurable activities less valued (Moore & Robinson, 2016). This interplay brings up significant issues concerning the linkage of organizational values and measured performance variables and the possible unintended consequences in the motivation and behaviour of employees.

The consequences of this for the roles and authority of HR should be considered.

The transformation of roles of HR is very much related to the transformation of the definition and assessment of performance. One of the main revelations in past research is the fact that AI has the potential to completely redefine HR roles and the very identity of HR professionals. The sociomaterial view of technology does not only shape human activity, but also contributes to the construction of organizational practices, responsibilities, and power relations (Orlikowski, 2007). This dynamic affects the way people work, how they perceive their roles and the influence of HR in the performance review process.

In this increasingly dynamic environment, HR could be more likely to act as the watch-dog over digital tools and as rule makers for how digital data can (or cannot) be used. HR departments could find themselves tasked with compliance, resolving employee concerns, and managing HR management's expectations for AI assessment. Therefore, AI can transform HR roles from subjective decision-making to monitoring, organizing and risk management (Tambe et al., 2019). New studies show that the impacts of AI-HRM can be both enabling and alienating (Talwar et al., 2026), indicating that the impacts of implementation are contingent.

Other studies show that the use of AI could lead to major changes in professional judgment. HR may gradually be losing the flexibility and discretion in their work, as HR algorithmic parameters are increasingly influencing the decisions they make (Talwar et al., 2026). At the same time, they might be expected to act as stewards of fairness and quality in the processes, having to trust the results of the process and be responsible for making sure the results are appropriate and in line with the organization's values (Nyathi, 2023). This can lead to role conflict and identity issues for HR professionals.

The literature has therefore shown that AI can improve, and at the same time overwork HR professionals. New studies have revealed that factors such as trust, fairness, transparency, and the

involvement of employees in the implementation of AI-driven HR systems play a crucial role in shaping the acceptance and effectiveness of these systems (Agung et al., 2024; Nyathi, 2023; Ying et al., 2025). The results indicated that the successful implementation is not only about technical sophistication but also about the sociotechnical integration, with the participation of the stakeholders.

Overall, the findings from these studies indicate that AI has the potential to revolutionize the assessment landscape, moving beyond simple technological progress to becoming a transformative organizational and professional paradigm shift. AI can make things faster and more consistent, but it also has the potential to fundamentally transform performance, its justification and how HR work is organized (Tambe et al., 2019; Kellogg et al., 2020). But less is known about the specifics of how such dynamics play out for HR professionals – why HR departments are turning to AI for performance assessment, and how embracing AI in turn changes the role, responsibilities, and decision-making power of HR. This thesis fills this void by exploring HR professionals' experiences and perspectives on the use of AI in performance evaluation, adding empirical analysis to the field that has been largely under-researched in the field of AI in HR.

Chapter 3. Theory

This study uses three complementary theoretical viewpoints to look at the integration of AI in HR performance assessment. Sociotechnical Systems Theory (Section 3.1) covers structural alignment of social and technical organizational parts. The practice lens, as SocioMateriality (Section 3.2) offers, can be used to examine the interaction of AI tools and human resources practices in daily work. The Digital Mindset framework (Section 3.3) provides a cognitive and behavioural approach to understanding the interpretation and action of individual HR professionals when it comes to AI outputs. These three levels are brought together in a coherent analytical framework in Section 3.4 which underlies the empirical analysis of this study.

3.1 Sociotechnical Systems Theory

This analysis is based on the theory of Sociotechnical Systems (STS) to go beyond the description of attitudes towards AI. STS offers an insight into structuring and interrelating of technology and human work, with the emphasis being on the interdependence of technical and social aspects in organizational systems.

STS theory began in the Tavistock Institute in the 1950s, and was the work of a particular investigation of longwall coal mining techniques by Trist and Bamforth (1951). They found that when a technical change was implemented without any change in social organization of the work, the productivity decreased, the stress level rose, and the working conditions worsened. In light of these results, STS postulated that each work system consists of two interdependent subsystems (Trist, 1981):

- Technical Subsystem includes the tools, machines, technologies and procedures. In this study, this is conceptualised as the use of AI tools for performance evaluation, appraisal

and decision making. Social Subsystem includes people, skills, roles, relations, norms, and values.

- This is a human element of HR that relates to empathy, ethical judgment, and communicating with others, which are challenging to automate and are key to the HR profession.
- Joint optimization is one of the main concepts in STS theory (Pasmore, 1995). Long-term success of a work system depends on a proper design and management of both the technical and the social subsystems. Sub-optimization (Cherns, 1987) is an approach in which the technology is optimized at the expense of the human well-being and autonomy, or the human needs are emphasized and the technology is not used sufficiently. In both cases the working life and the performance of the system are diminished.
- For HR, joint optimization is a combination of efficiency, predictive accuracy, data-informed decision making and the effects on the HR role, professional identity and experience. An AI HR system is only truly designed optimally if it enables HR professionals while simultaneously maintaining the ethics and human judgment, which is vital to HR processes. Despite being designed for an industrial application, STS is still applicable to digital transformation, algorithmic management, and human-robot interaction (Boström & Monks, 2024).

By integrating STS into the HR performance evaluation, several critical questions arise: How is the technical and social aspect configured in the design and implementation of AI evaluation systems? How much do HR people participate in the design of systems that impact HR? What role does AI play in HR practice, and how does it impact the equilibrium between human judgment and

technical efficiency? These questions will be used to guide the empirical research on HR professionals' experiences with AI implementation.

3.2 Sociomateriality

Wanda Orlikowski's (2007) sociomaterial theory of technology at work is also used in this study to further examine the use and experience of AI in relation to performance evaluations. Sociomateriality provides an unusual theoretical perspective on the dualism between technology and human action.

Orlikowski makes the point that there are limitations in organizational research with respect to the materiality of technology and how it is used in certain contexts. In a typical study, technology is considered as an external, static object (techno-centric approaches) or only as an object interpreted by the human subject, where technology may 'disappear' in sensemaking and social processes (human-centric approaches). Orlikowski notes that both strategies have certain drawbacks. The techno-centric perspective sees technology as a tool, a fact of life, and ignores the interpretation, use and modification of technological artifacts in practice. The focus on humans may overlook the material aspects of technology that influence opportunities for action and meaning making.

In this study, sociomateriality thus goes beyond STS theory, which emphasises the processes of mutual constitution of human and non-human elements rather than taking technology as a presupposed input to an otherwise social system. This view is that technology and human practice are intrinsic to each other and cannot be divorced from the continuous process of organizational practice.

The sociomaterial perspective shifts focus from the role of the HR tool in the creation of HR practice, to the role of the HR professional in using, interpreting and adapting the HR tool. In other

instances, such as when HR professionals rely on AI-based performance scores to evaluate employee work, they are not only using a tool for HR but a tool that is actively constitutionally participating in the HR process, affecting what's considered good performance and what's considered good decisions, what's considered fair, and what is not.

This view also sheds light on the dynamics of power in HR processes involving AI. Choices of performance indicators, algorithmic modeling, and design of system parameters are sociotechnical choices that involve particular views and values that privilege some and marginalize others. These decisions, built into systems of technologies, then impinge on organizational life in ways that are less salient to the users and/or evaluators of these technologies (Orlikowski, 2007).

3.3 The Digital Mindset

The Digital Mindset is a cognitive and behavioural approach that complements the STS and sociomaterial approaches, as introduced by Leonardo and Neeley (2022). In contrast to STS, which focuses on the integration of social and technical subsystems, and sociomateriality, which focuses on their integration in practice, the Digital Mindset is about thinking, foundational knowledge, and reasoning about data and AI work.

As Leonardi and Neeley (2022) state, "digital" is not a job title or technology field, it is a way of thinking. Data science and software engineering skills are not necessary for thriving in the digital age; rather, it's a specific mindset about how to utilize data, how algorithms work and go wrong, and how to collaborate via digital systems. Digital Mindset has a cognitive aspect as well as a behavioral aspect (Leonardi & Neeley, 2022).

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For the STS it is a prerequisite skill that allows HRs to ask questions, comprehend and affect the technical subsystem, instead of just adjusting to it. If HR professionals are not digitally literate, they may not possess the conceptual abilities to interact with the designers of the AI systems, to critically assess the outputs of an AI system, or to voice their concerns regarding design decisions that retain human judgment and ethical considerations in how the system is evaluated.

A digital mindset does not need to be the domain of technical experts and can be developed and shared (Leonardi & Neeley, 2022). Importantly, they highlight ethical and social issues like privacy, surveillance, fairness and employee well-being as core elements of a true digital approach, not an afterthought. When added to STS and sociomateriality, this digital mindset helps to understand how the same AI system can be optimized together in one HR context, but not in another, depending on the digital literacy of the HR professionals in the different contexts.

Digital mindset holds a special significance for this research because it focuses HR professionals on the skills, orientations, and readiness of HR in relation to the use of AI in performance assessment. Its conclusions highlight that the impact of implementing AI isn't just about the system design, but also about the knowledge and attitudes of HR professionals when it comes to engaging with technology.

3.4 Integrated Analytical Framework

Through STS theory, Orlikowski's sociomaterial theory, and Leonardi and Neeley's digital mindset framework, this study investigates three interrelated levels of AI integration in HR performance evaluation:

System Design Level (STS) focuses on structuring AI systems for HR and on linking together and optimizing the social and technical aspects. This level explores decisions made by organizations and designers that impact the scope and limitations of AI in the assessment of performance.

Practice Level (Sociomateriality) considers the use of AI in practice and the close relationship between humans and technology in practice. This level explores the practical application of AI in HR processes, such as the use, understanding and adaptation of technology in the profession.

Individual Level (Digital Mindset) is about attitudes and knowledge of HR professionals towards data and algorithms, their ethical sensitivity, and their ability to critically engage with the products of AI. The two subsystems identified by STS are concretized in the use of the systems in daily life as sociomaterial configurations in which the tools, practices, data platforms, norms, and expectations of AI are inter-woven and interdependent. How effective AI-based performance assessment is depends on HR professionals' and leaders' digital mindset.

HR professionals who see performance metrics as a trade-off and don't know how algorithms work or how data is generated are likely to overestimate AI's capabilities (assuming the algorithm can never be wrong or be subjective) or suffer from lack of trust (thinking that an algorithm is opaque or arbitrary), according to Leonardi and Neeley (2022). In both, sub-optimal results will likely be achieved. There are a number of analytical benefits with this integrated framework. First, it allows for analysis of AI implementation at different layers of analysis, from system design to individual practice. Second, it shows that these levels are inter-dependent, meaning that all three aspects have to be taken into account for the successful integration of AI. Third, it offers conceptual tools for comprehending the implementation outcomes in various organizational settings.

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