Exploring AI Adoption in Performance Management

From Anticipated Benefits to Challenges and Strategic Solutions

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By

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Executive Summary

The adoption of artificial intelligence (AI) in performance management, particularly among knowledge workers in traditional organizational settings, is the focal point of this thesis. The study aims to understand the current state of AI adoption, anticipated benefits, challenges, and effective strategies for adoption, considering the critical role of employees in this process. Performance management is crucial for employee motivation and overall performance, and its measurable nature aligns with AI's capabilities to enhance efficiency and objectivity. However, there is a gap in AI's adoption and perceived utility, indicating considerable resistance and skepticism.

From the outset, this study faced a unique challenge: no companies using AI in performance management agreed to participate. This underscores a broader reality; the topic is complex and shrouded in both excitement and secrecy. This reluctance highlights the sensitive nature of performance management. Moreover, the adoption of AI into human-centric processes is far from neutral. This study employs an exploratory qualitative research design, with data collected through semi-structured interviews with 15 HR managers and professionals who indirectly represented employees. Participants were selected from sectors actively engaging with AI technologies through direct implementation or consultancy services to capture diverse perspectives.

The findings reveal a nuanced perspective on the role of AI in performance management. While there is some use of generative AI tools, such as ChatGPT, the overall adoption remains minimal among companies in the Netherlands. HR professionals recognize AI's potential to enhance decision support, personalization and engagement, operational efficiency, and strategic planning. However, there is skepticism about AI's ability to fully capture employee performance, highlighting objectivity as both a benefit and a challenge. Key challenges identified include technology-, organization-, people-, and environment-related aspects. Among the challenges are diverse workforce perceptions, resistance to AI, and data quality issues. Assessing non-quantitative performance dimensions, such as competencies and skills, the variability in performance criteria, and the subjective nature of evaluations, remain significant hurdles. While AI offers data-driven insights, it does not yet solve these fundamental challenges in performance management.

Despite optimistic expectations, significant challenges persist in early stages of AI adoption in performance management, indicating the need for further research before widespread implementation can be achieved. Practically, this research provides valuable insights for HR managers, guiding them to critically assess their current technological landscape and evaluate the applicability of AI within their specific organizational context compared to other technologies. Companies should assess their performance management goals and criteria to determine if AI can effectively address these needs. The development of AI technology for performance management should be watched closely, as advancements could enable AI to automate more tasks. Effective AI adoption in performance management requires comprehensive strategies integrating technology, organization, people, and environmental factors during the initiation and adoption phases. Robust data management practices are essential to ensure the reliability and value of AI applications. Including employees in the process is vital for successful AI adoption. Additionally, maintaining a human touch is essential to ensure that technology enhances human capabilities rather than replaces them.

Shaped by the nascent stage of AI adoption in performance management, both in literature and practice, this study focused on theoretical explorations and anticipated challenges rather than real-world experiences. Future studies should focus on organizations actively adopting AI to assess whether the anticipated potentials, challenges, and strategies identified in this study hold in practice.

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1. Introduction

1.1 Background

AI is increasingly recognized as a revolutionary general-purpose technology with the potential to transform various sectors of the economy and society fundamentally. The development of AI has advanced significantly due to advancements in computational power, data availability, and algorithmic innovations, enabling machines to perform complex tasks ranging from pattern recognition to decision-making with unprecedented efficiency and accuracy (Vrontis et al., 2022). Despite significant advancements in AI, its practical application, especially in Human Resource Management (HRM), has not been extensively implemented. Algorithmic management research has primarily focused on digital labor platforms and the gig economy, leaving a significant gap in understanding its impact on traditional organizational settings (Bankins et al., 2024; Parent-Rocheleau & Parker, 2022; Pesole et al., 2020). Traditional workplaces are characterized by established hierarchical structures, centralized decision-making, and stability-focused operations, where human-driven labor management is predominant. Therefore, successfully adopting algorithmic management in these contexts depends heavily on its alignment with existing organizational practices and implementation methods.

HRM plays a pivotal role in value creation within organizations, balancing organizational goals with employee well-being. The digital transformation era has ushered in new opportunities and challenges for HRM, necessitating the reevaluation of traditional practices in light of technological advancements, which needs a supportive workforce to ensure a smoother adoption of technology and enhance the overall business value (Chowdhury et al., 2023).

A significant aspect of HRM is performance management, a strategic organizational process critical to employee motivation and overall performance. Performance management offers insights that drive decisions related to promotions, merit raises, transfers, and training initiatives (Basnet, 2024). By fostering employee commitment and satisfaction, it identifies areas for improvement, thereby enhancing productivity and organizational performance (Basnet, 2024). This continuous process of identifying, measuring, and developing individual performance aligned with organizational goals ensures that employee achievements contribute to broader strategic objectives, promoting recognition and performance enhancement (Aguinis, 2023).

Traditional performance management systems face criticism for their inefficiency, subjectivity, and periodic nature, which do not meet the modern-day desire to be dynamic. AI's real-time analysis and rating capabilities have the potential to introduce objectivity and efficiency in data collection, significantly influencing performance management strategies (Basnet, 2024; Buck & Morrow, 2018). However, tempering these discussions with a realistic understanding of AI's current capabilities and the empirical evidence supporting these claims is essential. Pan and Froese (2023) note that while AI is viewed positively in the computer science community for its analytical capabilities, management, and ethics, scholars are skeptical about AI's ability to fully capture the complex dynamics of human performance.

The intersection of AI and HRM is an emerging field focused on leveraging AI to enhance HRM functions, including performance management. However, the field lacks robust theoretical foundations and comprehensive empirical research, highlighting the need for further exploration to determine how AI can be effectively adopted into HRM practices and its implications for organizations and employees (Arslan et al., 2021; Garg et al., 2022; Pan & Froese, 2023; Tambe et al., 2019; Vrontis et al., 2022). This is further highlighted by a study involving senior managers on 152 AI projects, where 47% reported challenges in implementing AI with current employees, processes, and systems (Deloitte, 2017). The application of AI algorithms introduces complex ethical, practical, and conceptual dilemmas, mainly when data science analyses are applied to decisions about individuals, raising ethical and societal concerns (Tambe et al., 2019).

1.2 Problem Exploration

The application of AI in HRM is hindered by several barriers, including the complexity of HR phenomena, data limitations, ethical and legal constraints, and adverse employee reactions toward AI-driven decisions (Arslan et al., 2021; Tambe et al., 2019). Additionally, CEOs recognize organizational and employee resistance as significant obstacles to enterprise transformation (Malik et al., 2022). This resistance not only hampers the adoption of new technologies but also underscores the broader challenge of adapting organizational culture. Successful adoption of AI in HRM requires HR managers to perceive employees not just as end-users but as partners in the AI adoption process. This partnership is crucial for fostering acceptance and engagement, ensuring that employees are actively involved in the process (Arslan et al., 2021; Bamel et al., 2022; Fenwick et al., 2024; Leicht-Deobald et al., 2019; Tambe et al., 2019). Hence, a comprehensive understanding of the adoption process and the involvement of employees is essential.

Despite AI's potential to enhance HRM, the literature indicates employees' resistance to adopting AI into HRM practices (Arslan et al., 2021; Tambe et al., 2019). This resistance underscores the necessity of a nuanced approach to adopting AI within performance management, one that not only leverages the technological capabilities of AI but also addresses the human aspects of management and organizational culture. Additionally, the existing research predominantly focuses on the decision-makers and top managers, often neglecting the influence of employees who are directly impacted by AI-driven decisions (Langer & Landers, 2021). This oversight is significant because the success of AI systems in practice heavily depends on the reception and support from employees (Healy et al., 2020; Langer & Landers, 2021).

Despite its importance, performance management often receives less attention in AI-related HRM literature, which predominantly focuses on recruitment, onboarding, and employee engagement (Arslan et al., 2021; Garg et al., 2022; Prikshat et al., 2023). This oversight reveals a significant gap in the current literature, underscoring the need for focused research on AI's impact on performance management. Additionally, there seems to be significant potential, mainly attributable to performance management's measurable nature, which aligns well with AI's capabilities to enhance efficiency and objectivity in evaluations (Arslan et al., 2021; Garg et al., 2022). However, research highlights a notable gap in the adoption and perceived utility of AI in performance management, with respondents rating employee evaluation as the lowest area of AI support over the next five years, indicating considerable resistance and skepticism (Weber, 2023).

Moreover, there is a notable deficiency in research exploring strategies to mitigate the potential negative consequences of technology adoption in HRM functions, particularly considering the influence of employees within organizations (Budhwar et al., 2022). The literature underscores the need for strategies to address this challenge as these negative consequences can significantly impact the successful adoption of AI technologies (Arslan et al., 2021; Bankins et al., 2024; Budhwar et al., 2022; Malik et al., 2022).

In light of these challenges, this research aims to critically analyze the current state of AI adoption within performance management. The study will address the significant influence of employees on AI adoption processes and the resulting challenges. As AI continues to evolve in HRM, understanding and mitigating the impact of employee-related challenges is crucial for successful adoption (Bondarouk & Brewster, 2016; Fenwick et al., 2024; Park et al., 2021). This research seeks to fill the gap by proposing strategies to involve employees effectively and address potential barriers, ensuring a smoother and more effective adoption of AI technologies in performance management practices.

1.3 Research Objective

The primary objective of this research is to expand knowledge on the adoption of artificial intelligence in performance management, specifically focusing on knowledge workers in traditional organizational settings. The study will assess the extent to which organizations adopt or plan to adopt AI for performance management. It will determine the benefits organizations anticipate from integrating AI into performance management, identify their challenges, and propose strategies to adopt AI, considering employee roles and interests effectively.

This research aims to bridge the gap in the existing literature on AI in performance management and address the problem statement by providing valuable insights into the successful adoption of AI technologies in HRM. It will guide practitioners and scholars in navigating the future of work shaped by AI technologies.

The main research question is as follows:

How can artificial intelligence (AI) be effectively adopted into performance management practices?

Sub-questions:

1. To what extent are organizations currently adopting, or planning to adopt, AI into performance management?
2. What current opportunities are organizations anticipating to enhance performance management through the adoption of AI?
3. What hinders the adoption of AI for performance management within organizations?
4. What strategies can be employed to adopt AI into performance management while considering employee interests?

1.4 Report Structure

The structure of this master thesis is organized to present the research clearly and coherently. The Introduction section provides the background, explores the problem, and outlines the research objective. The Literature Review starts broadly with AI in HRM and then focuses on AI adoption in performance management, covering definitions, applications, promises, expectations, and challenges. The Methodology describes the research design, data collection, participant selection, validity, reliability, ethics, and data management considerations. The Findings section presents the current levels of AI adoption, potential benefits, challenges, and strategies for adopting AI into performance management. The Discussion analyzes the theoretical and practical implications of the findings, acknowledges limitations, and suggests future research directions. The Conclusion briefly summarizes the study. The report ends with References and Appendices that provide additional information and supporting documents.

2. Literature Review

2.1 AI in HRM

2.1.1 Definition of AI

AI remains a pivotal yet complex concept across various fields, marked by a lack of a universally accepted definition (Chowdhury et al., 2023; Kelly et al., 2023; Pan & Froese, 2023). This absence of consensus complicates the understanding and assessment of AI's impact on HRM.

The literature reflects diverse interpretations of AI, underlining its learning abilities, environment or external data interpretation, and autonomous operation. The wording is often different, where some scholars add specific focus, i.e., mimicking human cognitive tasks (Pan & Froese, 2023), focusing on specific goals through flexible adaptation (Arslan et al., 2021; Haenlein & Kaplan, 2019), or pattern recognition (Arslan et al., 2021). These characteristics highlight AI's capacity to perform tasks traditionally requiring human intelligence.

Chowdhury et al. (2023) and Pan and Froese (2023) have made notable contributions to address the definitional disparities. Chowdhury et al. (2023) derive a comprehensive definition from multiple disciplines, conceptualizing AI as "the ability of a manmade system comprising algorithms and software programs to identify, interpret, generate insights, and learn from the data sources to achieve specific predetermined goals and tasks" (Chowdhury et al., 2023). This definition emphasizes the synthetic nature of AI and its analytical and learning capabilities. Pan and Froese (2023) further distill AI's essence into its fundamental abilities, proposing AI as "artificial tools that can automatically accumulate experience and constantly learn from experience to perform cognitive tasks" (Pan & Froese, 2023).

In this research, the definition of AI by Pan and Froese (2023) is adopted due to its comprehensive encapsulation of AI's capabilities—learning, environmental interpretation, autonomous operation, and cognitive task performance (Pan & Froese, 2023). Pan and Froese's definition is based on abductive reasoning of the extant literature, synthesizing inconsistencies across 39 different definitions. This rigorous methodology ensures that the definition is theoretically sound and reflects a broad consensus within the academic community. Focusing on AI as tools that evolve through experience allows for a nuanced analysis of how AI technologies are perceived and utilized within the HR sector, making it the most relevant choice for this study.

2.1.2 Evolution of HRM

Human Resource Management (HRM) plays a pivotal role in the value creation processes within organizations, balancing organizational goals with employee well-being. HRM involves decisions on policies and practices that shape employment relationships, aiming for specific goals (Boselie et al., 2021). These goals encompass a spectrum of organizational outcomes, including improved organizational effectiveness and financial performance, as well as employee and societal-centric outcomes such as well-being. These are achieved through interconnected practices influencing various employee relationship facets (Boselie et al., 2021; Fenwick et al., 2024).

The field of HRM has undergone significant transformations due to technological advancements and changes in management practices. To fully appreciate the current state and anticipate future developments in HRM, it is crucial to explore its evolution, focusing on how HRM functions have adapted over time in response to new technologies and business needs.

The development of HRM can be categorized into several key phases (Fenwick et al., 2024; Vrontis et al., 2022; Zehir et al., 2020). Initially, HR focused mainly on administrative tasks using paper-based systems. This era, prevalent in the early to mid-20th century, utilized industrial psychology to enhance hiring and workplace efficiency. As the field evolved to personnel management, there was a shift toward managing employees as valuable assets, leading to the adoption of technologies like applicant tracking systems. This phase marked a move towards a more employee-oriented approach, incorporating training and development to improve employee skills, and electronic data processing makes an entrance to support manual record keeping of personnel data. From the late 20th century, HRM began to take on a more strategic role, leveraging technologies like electronic data processing systems, management information systems, and human resource information systems to align HR practices with organizational goals. This period is characterized by data-driven decision-making and efficiency. The latest phase, Business Partner HRM, includes digital HRM strategies that use technology to enhance the human experience at work. It stresses the importance of aligning technological solutions with human values to create organizational value and see HRM as a competitive advantage. The technologies include e-HRM and cloud-based HR software, and more recently, big data analytics, artificial intelligence, chatbots, and robotics.

Algorithmic management (AM) and Artificial Intelligence (AI) are now promising to transform HRM by leveraging data-driven approaches to optimize decision-making and enhance efficiency (Sahlin & Angelis, 2019; Tambe et al., 2019). AM utilizes algorithms to manage employee incentives and workflow, moving from traditional hypothesis-driven HR practices to a more dynamic, real-time analysis of workplace behaviors and outcomes. AI adds to this by analyzing vast datasets to predict trends and employee performance, enabling HR professionals to make proactive, informed decisions. These technologies could streamline HR processes and introduce new challenges in balancing efficiency with ethical considerations such as data privacy and the humanization of workplace practices (Jatobá et al., 2019; Palos-Sánchez et al., 2022).

Gartner's Hype Cycle for HR Technology provides a structured overview of these emerging technologies' maturity and adoption stages; see Figure 1 (Gartner, 2023). While the Hype Cycle faces significant scientific criticism and is not considered rigorous academic work, it is a practical tool widely used to navigate the landscape of new technology developments. AI-enabled skills management is currently in the "innovation trigger" phase, indicating the initial recognition of the technology's potential. However, it is expected to reach the "plateau of productivity" in 5-10 years, suggesting that widespread adoption and real-world benefits will take some time to materialize. In contrast, generative AI in HR is at the "peak of inflated expectations" and is predicted to mature in 2-5 years, suggesting that this technology receives significant attention and investment. However, it may currently be surrounded by hype and high expectations. Technologies like continuous employee performance management and machine learning in HR are both in the "trough of disillusionment." This phase reflects a period where early implementations have failed to meet expectations, leading to a reevaluation of their effectiveness. This stage is expected to last for 2-5 years before these technologies potentially emerge stronger with more realistic applications and benefits.

Interestingly, AI in talent acquisition is moving out of the "trough of disillusionment," indicating that despite early challenges, there is growing recognition of its value in improving recruitment processes. This technology is expected to reach maturity in 2-5 years, reflecting a more stable and productive phase where its benefits can be fully realized. This progression highlights the dynamic nature of technological adoption and the importance of tempering expectations with practical experience and results.

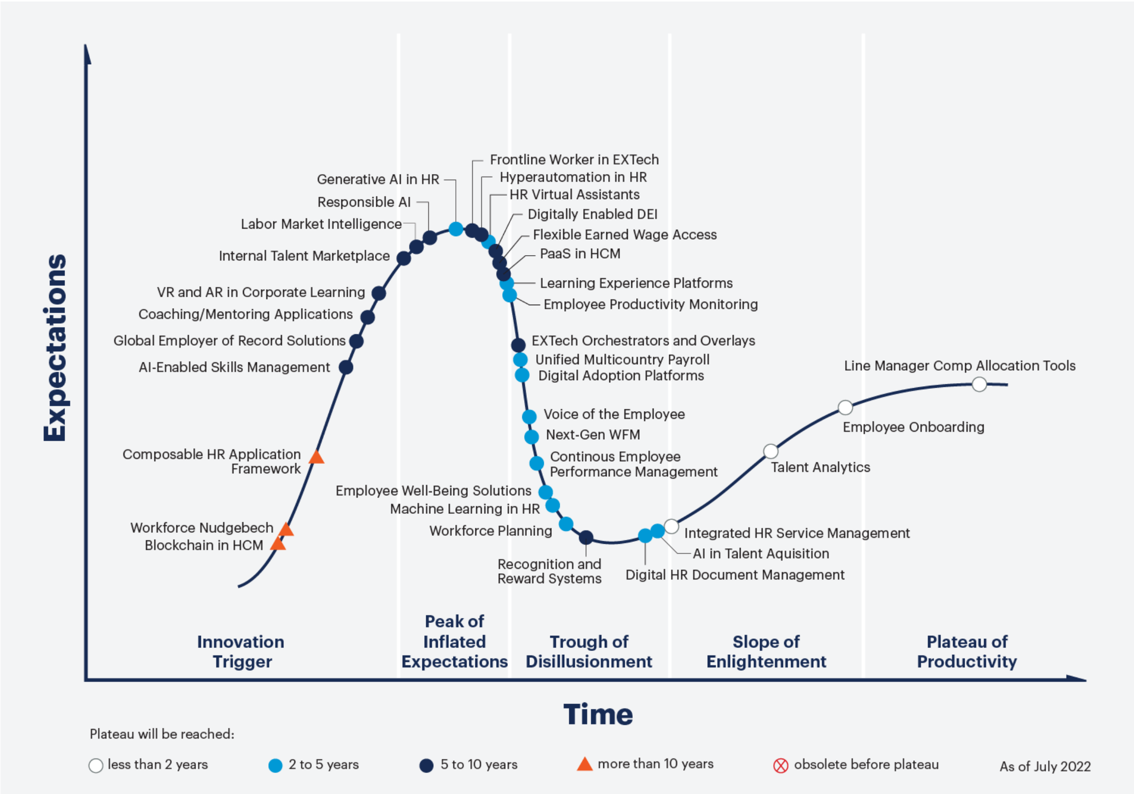

Figure 1. Gartner Hype Cycle for HR Technology. Source: Gartner (2023)

2.1.3 Application of AI Across HRM Functions

Artificial Intelligence (AI) holds substantial potential across various Human Resource Management (HRM) domains. In HRM, AI could revolutionize several key areas to optimize employee performance and ensure organizational success. Integrating information technology (IT) and HRM is crucial for enhancing business performance. Research indicates that while HRM capability directly influences business outcomes more significantly, IT capability also plays a crucial role by enhancing HR functions and indirectly supporting business performance (Zehir et al., 2020).

The adoption of AI in HRM is often associated with high expectations for transforming business strategies and improving organizational performance. These expectations are supported by claims that AI enhances automation, communication, and data-driven decision-making. AI technologies in HRM are advertised to lead to productivity gains, operational efficiencies, and improved customer engagement, ultimately reducing costs and increasing returns on investment (Budhwar et al., 2022; Palos-Sánchez et al., 2022; Rodgers et al., 2023; Zehir et al., 2020). The capability of digital HRM systems to convert data into actionable insights is critical for business (Zehir et al., 2020). AI is also envisioned as a strategic tool for supporting organizational policies and ensuring compliance (Rodgers et al., 2023).

AI technologies, notably intelligent chatbots, have been identified as valuable tools in enhancing HR communication. According to Rodgers et al. (2023), these AI applications help disseminate consistent organizational information and provide a holistic view of the entity to the workforce. Similarly, Palos-Sánchez et al. (2022) emphasize the enhanced interaction among employees facilitated by AI, suggesting improved organizational communication. AI-driven personalization in HRM, as outlined by researchers, provides significant benefits such as cost reductions and tailored employee experiences (Kaur & Kaur, 2022; Malik et al., 2022, 2023; Rodgers et al., 2023). These technologies enable HR departments to design personalized career paths, training programs, and benefits packages, directly contributing to increased job satisfaction and employee loyalty.

In recruitment and selection, AI technologies could streamline processes by automating the extraction and analysis of candidate information from resumes and social media (Budhwar et al., 2023; Garg et al., 2022; Pereira et al., 2023). Machine learning algorithms could improve matchmaking between job vacancies and candidates by evaluating personality traits, skills, and qualifications, promising more efficient and bias-reduced recruitment (Garg et al., 2022). AI tools like chatbots could enhance candidate experiences by providing real-time responses and personalized feedback (Chowdhury et al., 2023). While AI can potentially offer more objective and unbiased decisions (Richards et al., 2019), it also raises significant concerns rooted in the historical data used to train algorithms (Prikshat et al., 2022; Tambe et al., 2019). Often, this data reflects past biases and demographic disparities, leading to models that perpetuate these injustices. For example, the Amazon hiring algorithm disproportionately favored male candidates over females due to historical hiring patterns, illustrating how AI can inadvertently replicate past discrimination (Tambe et al., 2019). Such outcomes underscore the critical need for designing fair and unbiased algorithms.

During onboarding, AI through digital virtual assistants could play a crucial role in answering queries, guiding new hires, and recommending job-related content, thus speeding up and personalizing the onboarding process (Chowdhury et al., 2023).

For employee engagement, AI could analyze employee-related data to enhance engagement through text mining and sentiment analysis, helping tailor engagement practices to different groups and manage calendars, schedule meetings, and facilitate collaboration (Budhwar et al., 2023; Garg et al., 2022; Pereira et al., 2023).

AI could also assist in training and development by identifying training needs and recommending relevant courses, thereby personalizing the training process. Chatbots acting as personal career coaches could suggest training and readings, tailoring learning paths to individual aspirations and organizational needs (Budhwar et al., 2023; Garg et al., 2022; Pereira et al., 2023).

In compensation and benefits management, AI-driven systems could help HR professionals by tracking employee data to tailor compensation packages, ensuring fairness and alignment with organizational goals and employee expectations (Budhwar et al., 2023; Pereira et al., 2023; Zehir et al., 2020).

AI-based algorithms could predict employee turnover intentions by assessing work-related and employee-related factors, aiding in developing retention strategies (Budhwar et al., 2023; Garg et al., 2022).

AI could enhance team dynamics and HR planning by recommending team compositions and predicting performance. Analyzing team members' sentiments and interaction patterns could provide insights into team climate and roles, aiding strategic workforce planning roles (Budhwar et al., 2023; Garg et al., 2022; Pereira et al., 2023).

Lastly, in performance management, AI could, for example, automate performance evaluation, reducing costs associated with traditional methods. Machine learning algorithms could cluster employees based on performance and job satisfaction, aiding in developing strategies to improve performance and morale. However, caution is advised as automated performance management could impact motivation, especially among average performers who may prefer human assessors (Deloitte, 2024). The next chapter delves deeper into the potential and challenges of AI in performance management, exploring how it could transform this crucial aspect of HRM. For more context on AI in HRM, see Appendix C: Promises and Expectations of AI in HRM, which explores the multifaceted role of AI in HRM, distinguishing between the theoretical expectations and the empirical realities.

Artificial Intelligence (AI) is a game-changer in Human Resource Management (HRM), promising significant efficiencies and new capabilities. However, literature reveals a developing field with notable gaps between expectations and reality. Pan and Froese (2023) highlight that despite rapid growth, AI-HRM remains fragmented across disciplines with weak theoretical frameworks. Their review of 184 articles shows a lack of integration between computational sciences and management disciplines. There is a significant gap between AI tool development and its practical application in HR, with limited discussion on real-world effectiveness. Tambe et al. (2019) emphasize the disconnect between data science capabilities and HR operational knowledge. Data scientists excel in analytics but often lack HR-specific insights, while HR professionals may not fully understand the analytical methodologies of AI.

2.2 AI Adoption in Performance Management

Building upon the overview provided in the previous chapter on the impact of Artificial Intelligence (AI) within Human Resource Management (HRM), this chapter narrows down to a critical function within HRM: performance management. Rather than focusing on a specific tool or technology, the aim is to provide a general overview of the practical applications of AI in performance management. This will be illustrated with real-world examples from companies, highlighting both the practical implementations and the challenges associated with AI adoption in this context.

2.2.1 Promises and Expectations of AI in Performance Management

Performance management is a strategic organizational process that directly influences employee motivation and overall performance (Basnet, 2024). It provides insights that influence decisions regarding promotions, merit raises, transfers, and training and development initiatives. Furthermore, it fosters employee commitment satisfaction and identifies areas for improvement, thus enhancing overall productivity and organizational performance (Basnet, 2024). It involves continuous processes of identifying, measuring, and developing individual performance in alignment with organizational goals (Aguinis, 2023). This alignment ensures that employee achievements contribute to broader strategic objectives, fostering recognition and performance enhancement.

Several reasons drive the focus on performance management within the context of AI in HRM. While extensive research has been conducted on using artificial intelligence (AI) within Human Resource Management (HRM), there has been considerably less focus on performance management. Most of the literature emphasizes recruitment, onboarding, and employee engagement, with performance management often receiving less attention (Arslan et al., 2021; Garg et al., 2022; Prikshat et al., 2023). This oversight persists despite performance management being pivotal to organizational success, indicating a significant gap in current literature and practice. Additionally, there seems to be significant potential, mainly attributable to performance management's measurable nature, which aligns well with AI's capabilities to enhance efficiency and objectivity in evaluations (Arslan et al., 2021; Garg et al., 2022). Furthermore, research by Weber underscores a notable gap in the adoption and perceived utility of AI in performance management (Weber, 2023). Survey respondents rated the evaluation of employees as the lowest subarea regarding AI support within the next five years, highlighting considerable resistance and skepticism.

Modern performance management emphasizes continuous feedback and development, contrasting with traditional methods focused on setting standards and appraising past behavior (Cappelli et al., 2023; Sahlin & Angelis, 2019). Digitalization has revolutionized this field, facilitating efficient data collection, analysis, and feedback provision (Sahlin & Angelis, 2019; Vardalier, 2020). Performance management now assesses, motivates, and improves employee performance, fostering job satisfaction and organizational commitment (Basnet, 2024; Fenwick et al., 2024).

Traditional performance management systems are often critiqued for their inefficiency, subjectivity, and periodic nature, which do not align well with the modern-day desire to be dynamic. AI's real-time analysis and rating capabilities have the potential to introduce objectivity and efficiency in data collection, greatly influencing performance management strategies (Basnet, 2024; Buck & Morrow, 2018). However, tempering these discussions with a realistic understanding of AI's current capabilities and the empirical evidence supporting these claims is essential.

Buck and Morrow (2018) highlight the strategic importance of performance management in HR, suggesting that AI can significantly impact this area by providing more data-driven insights and real-time feedback mechanisms. Challenges associated with current performance management systems highlight the issues arising from the traditional approaches many organizations still employ. One of the primary concerns they note is the infrequency of feedback provided to employees. Traditional systems typically revolve around annual or semi-annual reviews, which can lead to significant delays in addressing performance issues and offering corrective guidance, thus potentially missing opportunities for timely improvements. Another significant challenge is the prevalence of bias and subjectivity in performance evaluations (Buck & Morrow, 2018). These evaluations often depend heavily on the perceptions and judgments of managers, which can introduce personal biases and lead to inconsistencies in how performance is assessed. This subjectivity undermines the fairness and transparency of the evaluations, potentially impacting employee morale and trust in the management process.

Moreover, Buck and Morrow (2018) point out that traditional performance management is time-consuming, involving extensive paperwork and manual processes, not only straining resources but also diverting managers' attention from more strategic activities. The administrative burden associated with traditional performance management systems can lead to delays and inefficiencies, further compounding the challenges of effectively managing employee performance. Through these observations, Buck and Morrow (2018) underscore AI's significant impact on performance management, suggesting that its integration could improve the accuracy and efficiency of systems and create a more engaged, motivated, and equitable workplace.

Despite the promising applications of AI, there is a significant gap in the empirical validation of its benefits in performance management. Pan and Froese (2023) note that while AI is viewed positively in the computer science community for its analytical capabilities, management and ethics scholars are skeptical about AI's ability to fully capture the complex dynamics of human performance. This skepticism underscores the need for AI systems to be transparent and explainable, especially when they significantly impact employee assessments (Pan & Froese, 2023; Prikshat et al., 2022).

AI offers several advantages that serve as drivers for its adoption. These include increased objectivity, reduced error rates, predictive capabilities for future behavior, enhanced work-related autonomy, creativity, innovation, and streamlined organizational processes (Chowdhury et al., 2023; Giermindl et al., 2022; Malik et al., 2023). AI's monitoring capabilities can enhance performance measurement, track employee morale, and aid retention strategies by analyzing social media data (Chowdhury et al., 2023; Gaur & Riaz, 2019). Operational efficiency gains, cost reductions, and enhanced business productivity are significant drivers of AI adoption (Chowdhury et al., 2023; Gaur & Riaz, 2019; Malik et al., 2023)

AI could redefine performance management by transitioning from traditional annual reviews to continuous feedback loops (Buck & Morrow, 2018; Choudhary, 2022; Zehir et al., 2020). These AI-driven systems enable real-time feedback mechanisms, offering employees immediate insights into their strengths and areas for improvement. By analyzing various data sources, including project outcomes and peer interactions, AI algorithms generate comprehensive performance profiles that foster employee growth and adaptability in fast-paced work environments (Choudhary, 2022; Wamba-Taguimdje et al., 2020). This dynamic approach to feedback, rather than periodic reviews, supports a more agile and responsive organizational culture.

AI can aid in optimizing performance management processes by collecting and analyzing real-time employee performance data. This capability allows for objective evaluations and personalized feedback, promoting fairness and reducing biases traditionally associated with human evaluations (Choudhary, 2022; Madanchian et al., 2023; Richards et al., 2019). Moreover, powered by predictive analytics, AI can revolutionize performance evaluation by forecasting future trends based on historical data patterns. These analytics help HR professionals anticipate potential performance roadblocks and proactively design interventions, ensuring that performance goals are realistically tailored to an employee's capabilities and role requirements.

Building on theories of decision-making and recent research on data-driven HR management, AI algorithms, and expert systems are found to facilitate HR processes and enhance the accuracy of HRM decisions made by non-experts (Prikshat et al., 2022; Vrontis et al., 2022). By eliminating time-consuming decision-making processes, AI strengthens the quality of HR decisions, allowing for quicker and more effective responses to HR needs. Additionally, AI identifies skill gaps and offers targeted training and development opportunities, which is crucial for improving employee performance outcomes (Buck & Morrow, 2018).

Research indicates that performance management systems powered by AI have improved worker engagement and output (Buck & Morrow, 2018; Richards et al., 2019). AI enhances performance management by providing more meaningful and relevant feedback, which has been shown to increase employee engagement and ensure that performance evaluations are more accurate and fair than traditional methods. This improvement in the quality of feedback and the fairness of evaluations contributes significantly to boosting morale and productivity in the workplace.

2.2.2 AI Applications in Performance Management

The current AI applications are discussed to provide a broad and practical perspective on enhancing traditional performance management methods. This overview does not focus on one specific tool or technology but aims to cover a range of practical applications at a higher level. It is essential to acknowledge that while AI offers promising solutions, its practical application in performance management is still evolving. The extent to which AI can truly enhance these processes depends on various factors, including technological advancement, organizational readiness, and the alignment of AI tools with specific performance management goals (Chowdhury et al., 2023; Prikshat et al., 2023). Additionally, there is an ambiguity surrounding AI tools, with uncertainties about whether a tool genuinely leverages AI or merely incorporates AI as a buzzword to enhance its market appeal. This ambiguity can lead to misaligned expectations. To address this issue, this analysis includes only those tools for which substantial information is available regarding their AI functionalities, ensuring a focused and accurate assessment of how AI can effectively contribute to performance management. Thus, the objective is not to assert that AI will solve all challenges inherent in performance management but to examine how AI could theoretically augment tasks. Moreover, details on how exactly AI is integrated into performance management are often lacking, including the specific data used to train and develop these tools. The examples provided here include data from both internal sources and third-party databases.

Organizations are currently adopting AI into performance management to varying extents. One application of AI in performance management is the integration of diverse performance-related data sources to provide a holistic view of employee performance. For instance, IBM has implemented an analytics-driven solution to infer employee expertise by analyzing enterprise and social data (Varshney et al., 2014). This system integrates data from various sources, such as job titles, HR information, social tags, and work product data, to predict employees' job roles and specialty areas. The data includes features from enterprise systems of record and data from the internal corporate social networking site IBM Connections. To estimate generalization accuracy, the researchers performed cross-validation. There is no reason to suspect any systemic bias in employees where not all data points are clear, ensuring that the model's predictions remain robust and reliable. By approaching the prediction of job roles and specialties as a supervised classification problem, IBM's AI system ensures that performance expectations are set based on accurate and up-to-date expertise assessments.

Another example is the Talent Intelligence Hub in the SAP SuccessFactors Human Experience Management Suite, which leverages AI to enhance performance assessment through a skills-based approach to talent management (Russo, 2023). This hub shifts the focus from job titles and academic qualifications to understanding an individual's skills. It integrates data from internal records and third-party databases to develop detailed employee skills profiles, encompassing performance evaluations, training histories, and self-reported skills and preferences. This dynamic skills framework aligns employee skills with organizational needs, fostering growth and adaptability, and provides a comprehensive skills inventory to support informed decision-making in talent management.

IBM has also developed an AI-driven system to enhance the summative performance evaluation process (Horesh et al., 2016). This system targets specific areas of expertise and employs an information retrieval component to intelligently index and search enterprise data. Using machine learning technologies, it accurately labels employees with their corresponding levels of expertise, ensuring a nuanced understanding of employee skills across the organization.

These three examples are intended to give an impression of how organizations currently adopt AI in performance management. For more examples, see Appendix B: AI Technologies in HRM for AI technologies and Appendix D: Breakdown of Performance Management Cycle and Tasks with Examples for real-life applications.

2.2.3 Challenges in AI Adoption in Performance Management

The adoption of Artificial Intelligence (AI) in performance management is a growing trend, reflecting an emerging shift within organizational practices. This transition, characterized by gradual acceptance and integration, highlights the nascent nature of AI in managing and enhancing performance. The term "adoption" suggests a gradual and evaluative process of acceptance and integration, reflecting the current state of AI in this domain, where organizations are still exploring its potential benefits and limitations. Most research on AI adoption focuses broadly on HRM. Therefore, this review examines HRM adoption and specific performance management aspects to provide a comprehensive overview.

The research by Prikshat (2023) and Fenwick (2024), though coming from different focal points, synergistically overlaps, especially at the initial stages of AI adoption in HRM. This alignment is significant as both perspectives underscore these early stages' foundational role in setting the trajectory for more advanced AI integration in HR practices.

Prikshat's (2023) framework begins with the initiation stage, emphasizing awareness and evaluation of potential AI benefits in HRM, naturally leading to the adoption stage. Here, the focus is on assessing organizational needs, the capabilities of AI technology, and the availability of necessary resources. This stage is critical for understanding the specific functionalities of AI that can be leveraged for HR tasks and ensuring these technologies align well with organizational goals and existing processes.

Fenwick's (2024) discussion of the technocratic phase aligns with this as it represents the initial tangible integration of AI into HRM operations. It moves beyond theoretical assessment to actual application, focusing on using AI to automate and enhance specific HR functions such as recruitment and performance management. This phase practically demonstrates the theories and assessments conducted in Prikshat's (2023) initiation and adoption stages.

According to Vrontis et al. (2022), the novelty of AI in HRM presents significant methodological and ethical challenges. These issues are expected to be progressively addressed as the integration of AI into HR practices evolves. Additionally, Singh and Pandey (2024) note that while AI in HRM is gaining attention, the existing literature remains sparse and disjointed. Most studies have not directly addressed the enablers and barriers to AI adoption within HR ecosystems, highlighting a significant gap in understanding how AI can be effectively integrated into HRM strategies. Rodgers et al. (2023) emphasize that HRM teams must stay abreast of AI advancements to maintain a competitive edge in talent acquisition and management. From HRM to performance management, Tambe et al. (2019) suggest prioritizing HR tasks that are more amenable to data science applications, such as analyzing open-ended employee feedback through natural language processing. This approach helps identify patterns and insights that can significantly enhance performance management practices without the complexities associated with more sensitive HR functions like hiring.

The challenge of employee reaction to AI adoption is multifaceted. Pan and Froese (2023) emphasize that many employees are not yet ready to work with AI, necessitating a focus on AI-employee integration, job redesign, and training, supported by a culture of open-mindedness for successful implementation. Tambe et al. (2019) and Singh and Pandey (2024) identify employee fears such as job loss and lack of control as significant barriers to AI adoption, highlighting the necessity of involving employees in the process. Addressing these fears and ensuring ethical considerations, privacy, and data protection are crucial. The current focus on understanding initial employee perceptions of AI is essential for navigating early AI adoption stages and addressing potential resistance, with research indicating that positive perceptions and early involvement are crucial for successful AI integration in HRM, leading to increased satisfaction and performance (Charlwood & Guenole, 2022; Den Hartog et al., 2013; Leicht-Deobald et al., 2019; Tambe et al., 2019; Vrontis et al., 2022). Successful AI integration thus hinges on preparing and supporting employees, fostering a data-centric culture, and minimizing resistance by involving employees in the adoption process, which can enhance productivity and resilience (Chowdhury et al., 2023).

While AI has the potential to provide more objective and unbiased performance assessments (Richards et al., 2019), the historical data used to train these algorithms often reflect past biases and demographic disparities, leading to models that perpetuate these injustices (Prikshat et al., 2022; Tambe et al., 2019). Ensuring fairness in AI-driven evaluations requires rigorous testing against the criteria of distributive, procedural, interactional, and relational justice (Greenberg, 2004). Employees must trust that AI evaluations are fair, transparent, and accurately reflect their performance, as procedural fairness is crucial in maintaining job satisfaction and morale (Pan & Froese, 2023). However, misunderstandings or non-acceptance of AI-driven decisions can lead to adversarial organizational behaviors, negatively impacting outcomes (Tambe et al., 2019). Studies indicate a spectrum of attitudes among employees toward AI, encompassing both positive and negative sentiments (Arslan et al., 2021; Bankins et al., 2024; Budhwar et al., 2022; Palos-Sánchez et al., 2022). Effective communication and understanding are pivotal in mitigating adverse reactions to AI adoption. Scholars emphasize the importance of ensuring employees comprehend AI-based decision-making processes to prevent adversarial behaviors (Budhwar et al., 2022). However, limited research exists on strategies to mitigate the negative consequences of technology adaptations in HRM functions (Budhwar et al., 2022).

Closely related to fairness is the challenge of explainability, focusing on the transparency and comprehensibility of AI-driven decisions. In performance management, employees must understand the criteria and reasoning behind their evaluations (Prikshat et al., 2022; Tambe et al., 2019). Though potentially more accurate, complex algorithms often lack transparency, leading to dissatisfaction and perceived unfairness among employees, even when the algorithms are unbiased. Additionally, AI can embed and perpetuate existing biases, raising ethical and legal concerns (Chowdhury et al., 2023; Kellogg et al., 2020). The adoption of AI in HRM requires organizations to ensure transparent communication about the data collected and its impact on employee decisions and rights, addressing the ethical and legal standards necessary to protect employees' interests (Budhwar et al., 2022; Fenwick et al., 2024; Tambe et al., 2019).

The use of AI in performance management also raises substantial ethical and data privacy issues (Kellogg et al., 2020; Maheshwari et al., 2017; Pasha & Poister, 2017). AI systems can track professional performance, personal attributes, and behaviors, extending employer control beyond workplace hours. For instance, some companies employ wearable devices that monitor employees' lifestyle choices, including physical activities and sleep patterns, thus blurring the lines between work and personal life (Kellogg et al., 2020). This extensive monitoring can lead to constant surveillance, negatively impacting employee morale and job satisfaction (Fenwick et al., 2024; Giermindl et al., 2022; Kellogg et al., 2020; Parker & Grote, 2022). Moreover, the right to privacy and data protection is complicated by AI, necessitating robust legal frameworks like the GDPR and the forthcoming EU AI Act (*AI Act*, 2024; Tambe et al., 2019). The EU AI Act attempts to address these issues by categorizing AI systems based on risk and imposing strict regulations on high-risk applications. This act mandates transparency, enhances data governance, and ensures compliance with ethical and legal standards, particularly in sensitive areas such as recruitment and performance evaluation (*AI Act*, 2024). These regulations aim to ensure compliance with ethical and legal standards but pose considerable challenges, particularly for small and medium-sized enterprises (SMEs), which may struggle with the technical expertise and resources required for compliance. Consequently, while these regulations strive to address critical ethical concerns, they also potentially slow the innovative use of AI in HR practices across different business landscapes (Arslan et al., 2021; Bamel et al., 2022; Budhwar et al., 2022).

Defining what constitutes a 'good employee' is particularly challenging due to the complexity and variability of job roles across different contexts, although critical to the effectiveness of AI in performance management (Tambe et al., 2019). AI systems depend heavily on data from performance appraisals, often criticized for their validity and potential biases, perpetuating flawed human judgments (Tambe et al., 2019). Traditional metrics frequently fail to capture the full range of individual contributions, particularly in team-oriented roles, exacerbating the difficulty of establishing universal evaluation criteria. The subjective nature of many performance indicators further complicates assessments, often resulting in incomplete and biased measures that undermine HR operations (Tambe et al., 2019). The complexity is further accentuated by the digital traceability of HR actions, where not all operations leave digital footprints easily convertible into actionable data (Tambe et al., 2019). Moreover, AI's focus on quantifiable data can overlook critical qualitative aspects like moral standards and emotional intelligence, which are essential for comprehensively evaluating HR performance (Pan & Froese, 2023). This challenge is compounded by the ethical concerns surrounding data-driven evaluations, which can inadequately reflect the holistic value of employees due to their reliance on easily measurable data.

Data quality emerges as a central concern when deploying AI in HRM. High-quality data is essential for accurate algorithmic outputs; otherwise, biases can lead to unfair employee evaluations and retention decisions. It is not easy to verify the accuracy of data from large pools (Chowdhury et al., 2023; Kellogg et al., 2020). Small organizations often struggle because their data sets are not extensive or robust enough, exacerbating the risk of biased and ineffective decision-making (Basu et al., 2023). The rarity of critical HR events like dismissals further compromises the effectiveness of AI systems in HRM. Tambe et al. (2019) highlight that AI often fails to predict these outcomes due to insufficient observational data. Therefore, the precision and impact of AI in performance management heavily depend on the quality and quantity of training data, without which the objectivity AI is supposed to offer remains unfulfilled (Basnet, 2024; Tambe et al., 2019).

Technological infrastructure is crucial for the effective integration of AI in HR functions. As Prikshat (2023) noted, organizations must continually update their Information Technology (IT) systems to keep pace with evolving AI technologies, which support various HR activities, from performance evaluation to strategic decision-making. It highlights the necessity for extending IT systems to incorporate new-generation Business Intelligence systems, reinforcing the alliance between technology and HR (Prikshat et al., 2023). Technological readiness represents a firm's capacity to deploy technological assets effectively. Organizations with a higher degree of technological readiness are better equipped to swiftly assess, prepare, and integrate AI technologies into their operational framework (Makarius et al., 2020). Effective AI integration requires understanding AI processes (Chowdhury et al., 2023). AI systems in HRM lack transparency, making it difficult for decision-makers to trust or understand AI-generated outcomes, and managers often lack complete comprehension of AI impacts, which hinders system efficacy (Budhwar et al., 2022; Chowdhury et al., 2023; Fenwick et al., 2024).

Dynamic IT capabilities are increasingly critical in the context of AI adoption. These capabilities, such as dynamic digital platform capability and dynamic IT management capability, facilitate AI application initiation, adoption, and routinization (Prikshat et al., 2023). Organizations with strong dynamic capabilities are better positioned to adopt AI effectively across different HR functions.

AI's predictive and analytical capabilities, while robust, face significant challenges when dealing with the nuances of human behavior and the unpredictability of external environmental factors. Chowdhury et al. (2023) noted that AI systems can efficiently identify patterns in employee performance data. However, their ability to discern the underlying reasons for performance discrepancies is limited. This limitation stems primarily from AI's lack of creative and social intelligence, crucial for understanding complex, often subtle human behaviors and motivations. In line with this, the adoption of AI technologies within organizations is significantly influenced by the perceptions of the technology. When the technology is not deemed applicable, the adoption could be hindered (Bankins et al., 2024; Prikshat et al., 2023).

Organizational readiness is crucial for successfully adopting AI in HRM (Chowdhury et al., 2023). It encompasses the preparedness and availability of necessary resources, significantly influencing AI technologies' assimilation. Studies suggest that organizational readiness strongly predicts technology adoption success, highlighting its importance in HRM transformation (Bondarouk et al., 2017; Gupta et al., 2020; Zhu et al., 2006). Organizational characteristics also play a pivotal role, with specific traits affecting Information Technology (IT) and Information System (IS) applications significantly (Bondarouk et al., 2017; Gupta et al., 2020; Zhu et al., 2006).

Top management's support is critical in successfully adopting and implementing complex IS (Bankins et al., 2024; Prikshat et al., 2023). High levels of management support indicate an understanding of the benefits of new AI techniques and provide necessary political and motivational support throughout the technology assimilation lifecycle. Supervisor support plays a crucial role during the stages of AI-HRM assimilation. Supervisors impact adoption through their use and advocacy of new technologies (Prikshat et al., 2023). Their ability to contextualize AI applications within HR activities enhances understanding and uptake among HR personnel and employees.

Adopting AI in HRM involves overcoming numerous challenges, including cultural adaptation (Arslan et al., 2021; Fenwick et al., 2024). Also, cultural awareness's importance in AI implementations suggests that global organizations must tailor AI tools to diverse workplace environments. The pace of technological change demands a shift towards a data-centric culture within organizations (Chowdhury et al., 2023). This cultural transformation is essential for the effective implementation and utilization of AI, where all organizational members are aligned and supportive of AI strategies. The approach to AI adoption can significantly affect its success. A collective, organizationally driven decision-making process is generally seen as more beneficial than approaches that rely on individual initiatives (Bankins et al., 2024; Basu et al., 2023). Furthermore, engaging employees in the AI life cycle can mitigate resistance and enhance acceptance of AI systems (Tambe et al., 2019).

AI's influence on the traditional supervisor-subordinate relationship raises questions about the dynamics of social exchange. Traditionally, this relationship is pivotal to employee performance, where mutual support between supervisor and subordinate fosters job satisfaction and productivity (Tambe et al., 2019). However, introducing AI can alter these dynamics, potentially diminishing the personal touch that supervisors provide. Rodgers et al. (2023) further emphasize the importance of understanding how employees perceive their organizational roles. Such perceptions can significantly influence employee commitment and integrity within the organization.

HR employees' ICT skills significantly influence AI adoption in HRM. The ability to design, operate, and maintain AI-driven functions requires a high level of digital literacy and technical expertise, and a robust ICT skill set facilitates the effective assimilation of new technologies (Malik et al., 2022; Prikshat et al., 2023). The willingness to adopt and experiment with innovative AI-HRM techniques correlates with a higher degree of personal innovativeness. Individuals with innovative attitudes are likelier to engage with and normalize new technologies in their workflow (Agarwal, 2022; Prikshat et al., 2023).

Additionally, the degree of human involvement is an essential factor influencing how people perceive AI in HRM (Bankins et al., 2024; Chowdhury et al., 2023; Fenwick et al., 2024). The collaboration between human judgment and AI in decision-making processes often enhances the acceptance and perceived fairness of AI applications in performance management (Budhwar et al., 2022; Fenwick et al., 2024). Research emphasizes that augmented decision-making improves acceptance of AI outputs, where AI supports rather than replaces human decisions (Bankins et al., 2024). This method has been particularly effective in recruitment, increasing job offer acceptance rates. However, familiarity with

AI can moderate this effect, with those accustomed to AI showing less preference for humans over AI recruiters (Langer & Landers, 2021).

The literature presents divergent views regarding whether people perceive algorithms as more objective than humans in decision-making. While some perceive algorithms as structured and quantitatively driven, holding less negative intentionality, others argue that this perception could lead to overly reductive decision-making processes. Bankins et al. (2024) suggest that algorithms are generally viewed as more objective and less biased than humans, recommending that workers adhere to system rules for fair performance evaluation. Langer and Landers (2021) emphasize the efficiency and objectivity of automated evaluation in algorithmic management contexts, advocating for its adoption. Chowdhury et al. (2023) identify significant drivers for AI adoption, including the potential for objectivity, reduced likelihood of mistakes, and predictive capabilities based on historical data patterns.

Despite the perceived objectivity of algorithms, studies suggest that people generally view human decision-making as more nuanced, holistic, and adaptive to qualitative information (Chowdhury et al., 2023). Langer and Landers (2021) found that automated decisions are often perceived as less fair than human decisions across various scenarios. Despite its nuanced nature, Bankins et al. (2024) highlight the potential biases and less objective outcomes of human decision-making. Perceptions of algorithmic versus human decisions are influenced by task characteristics, with tasks requiring human skills, leading to less trust, fairness, and positive emotions toward algorithmic decisions. Lee (2018) suggests that algorithmic decisions are perceived as less fair and trustworthy for tasks requiring human skills. However, some perceive them positively due to their role in preventing favoritism and biases.

Individual characteristics significantly influence employees' attitudes toward AI (Bankins et al., 2024; Makarius et al., 2020). Gender, task performance, and locus of control shape perceptions of AI's efficacy and impact on employment prospects (Bankins et al., 2024). For instance, individuals with higher task performance may prefer algorithmic recruiters for their perceived competence in assessing quantitative metrics. In comparison, those with lower task performance may favor human recruiters for their qualitative assessment abilities (Bankins et al., 2024).

Research into adopting talent acquisition indicates that support from AI technology vendors is crucial when organizations adopt AI technologies for talent acquisition. However, Pillai and Sivathanu (2020) highlight that this adoption is contingent on the availability and involvement of technology vendors who provide the necessary AI tools and customize these tools to meet specific organizational needs. HR managers often lack the technical expertise to deploy AI effectively, necessitating vendor involvement for tool provision and customization, particularly when the organization opts to 'buy' rather than 'build' its AI solutions.

Competitive pressure is another environmental factor critical to adopting AI in HRM. According to a report by Deloitte (2017), competitive forces can compel organizations to adopt new HR technologies. This pressure stems from the need to survive and thrive in a competitive industry, where staying abreast of technological advancements is crucial. The influence of competitive pressure on organizational technology decisions highlights the external environment's role in shaping strategic technological investments (Pillai & Sivathanu, 2020).

To provide a clearer and more accessible summary, Table 1 offers an overview of the challenges identified in the literature.

Table 1. Overview of challenges identified in the literature

Challenge	Description	Source
Employee Reactions and Integration	Employees' readiness, fear of job loss, and lack of control are significant barriers.	Singh and Pandey (2024); Tambe et al. (2019)
Fairness and Bias	AI systems can perpetuate past biases in historical data, requiring rigorous testing for fairness and evaluation transparency.	Greenberg (2004); Prikshat et al. (2022); Tambe et al. (2019)
Explainability	There is a need for transparency and comprehensibility of AI-driven decisions; lack of transparency can lead to dissatisfaction and perceived unfairness among employees.	Prikshat et al. (2022); Tambe et al. (2019);
Ethical and Data Privacy Issues	AI's extensive monitoring raises ethical and data privacy concerns, potentially impacting employee morale and job satisfaction.	Fenwick et al. (2024); Giermindl et al. (2022); Kellogg et al. (2020); Maheshwari et al. (2017); Pasha & Poister (2017); Parker and Grote (2022);
Defining a 'Good Employee'	Defining a 'good employee' is challenging due to the complexity and variability of job roles.	Pan and Froese (2023); Tambe et al. (2019)
Inadequate Metrics to Measure Human Behavior	Traditional metrics often fail to capture the full range of individual contributions, and not all HR operations leave digital footprints that are readily convertible into actionable data.	Chowdhury et al. (2023); Tambe et al. (2019)
Quality and Quantity of Data	High-quality data is essential for accurate AI outputs; organizations struggle with inadequate data sets.	Basu et al. (2023); Chowdhury et al. (2023); Kellogg et al. (2020); Tambe et al. (2019)
Technological Infrastructure	Continuous updates of IT systems are crucial for effective AI integration in HR functions.	Chowdhury et al. (2023); Prikshat et al. (2023)
Technological Readiness	Firm's capacity to deploy technological assets effectively.	Budhwar et al. (2022); Chowdhury et al. (2023); Fenwick et al. (2024); Makarius et al. (2020)
Dynamic IT Capabilities	Dynamic IT capabilities facilitate AI application initiation, adoption, and routinization.	Prikshat et al. (2023)
Perceptions of AI	Perceptions of AI's efficacy and applicability could hinder adoption.	Bankins et al. (2024); Prikshat et al. (2023)
Organizational Readiness	Organizational readiness is crucial for successful AI adoption and implementation.	Bankins et al. (2024); Bondarouk et al. (2017); Chowdhury et al. (2023); Gupta et al. (2020); Zhu (2006)
Top Management Support	Top management's support is critical for the successful adoption, providing the necessary political and motivational support.	Bankins et al. (2024); Prikshat et al. (2023)

Supervisor Support	Supervisor support impacts adoption through their use and advocacy of new technologies.	Prikshat et al. (2023)
Cultural Adaptation	Organizations must tailor AI tools to diverse workplace environments, emphasizing cultural awareness and fostering a data-centric culture for effective AI implementation.	Arslan et al. (2021); Chowdhury et al. (2023); Fenwick et al. (2024)
Dynamics of Social Exchange	The introduction of AI can alter the traditional supervisor-subordinate relationship, potentially diminishing the personal touch provided by supervisors and affecting employee commitment and organizational integrity.	Rodgers et al. (2023); Tambe et al. (2019)
ICT Skills of HR Employees	HR employees' ICT skills significantly influence AI adoption, requiring high levels of digital literacy and technical expertise for effective AI-driven functions.	Malik et al. (2022); Prikshat et al. (2023)
Degree of Human Involvement	The level of human involvement in AI decision-making processes influences employee acceptance and perceived fairness of AI applications, with augmented decision-making enhancing overall acceptance.	Bankins et al. (2024); Budhwar et al. (2022); Chowdhury et al. (2023); Fenwick et al. (2024)
Objectivity	The perception of AI algorithms as objective can influence their acceptance; however, this perception can lead to overly reductive decision-making, missing the nuanced, holistic understanding that human decision-making provides.	Bankins et al. (2024); Chowdhury et al. (2023); Langer and Landers (2021)
Individual Characteristics	Employees' attitudes towards AI are significantly influenced by individual characteristics such as gender, task performance, and locus of control.	Bankins et al. (2024); Makarius et al. (2020)
Vendor Support	Support from AI technology vendors is crucial for adequate AI tool provision and customization, particularly when organizations opt to 'buy' rather than 'build' AI solutions.	Pillai and Sivathanu (2020)
Competitive Pressure	Competitive forces compel organizations to adopt new HR technologies to maintain a competitive edge.	Deloitte (2017); Pillai and Sivathanu (2020)

The interdisciplinary review by Pan and Froese (2023) reveals a significant gap in utilizing theoretical constructs in studies focusing on AI and HRM. Specifically, only 21% of such studies employ robust theoretical frameworks. This research aims to address this gap by leveraging comprehensive theoretical lenses to explore the adoption of AI in performance management, thereby contributing to the theoretical rigor in AI-HRM research.

Three pivotal theories underpin modern performance management practices (Armstrong & Taylor, 2014). Latham and Locke's Goal Theory posits that clear, challenging goals facilitate performance by focusing attention, stimulating effort, and leveraging individual skills (Latham & Locke, 1979). This theory supports the performance management focus on setting and agreeing on objectives to measure and manage performance effectively. Emphasizing the significance of feedback, Control Theory describes how individuals adjust their behavior in response to feedback to minimize discrepancies between actual and expected performance (Armstrong & Taylor, 2014). This theory underscores the critical role of feedback within the performance management cycle. Bandura's Social Cognitive Theory introduces the concept of self-efficacy, suggesting that individuals' beliefs in their capabilities significantly influence their performance (Bandura, 1986). Strengthening self-efficacy is, therefore, a crucial objective in performance management, aiming to empower employees and enhance their performance potential.

This study employs the Technology-Organization-Environment (TOE) and Technology-Organization-People (TOP) theories as theoretical lenses to guide the research and structure the interviews. The TOE theory considers the technological, organizational, and environmental contexts that influence the adoption and implementation of innovations such as AI (Pathak & Bansal, 2024; Pillai & Sivathanu, 2020; Prikshat et al., 2023). However, recent studies emphasize the importance of incorporating people factors, leading to the TOP theory's emergence (Bondarouk et al., 2017; Gupta et al., 2020; Prikshat et al., 2023; Stevens, 1989). The TOP theory addresses this gap by explicitly considering human aspects.

Both the TOP and TOE theories are increasingly recognized for their relevance in AI adoption and HRM contexts (Basu et al., 2023; Bondarouk et al., 2017; Gupta et al., 2020; Pan & Froese, 2023; Pathak & Bansal, 2024; Pillai & Sivathanu, 2020; Prikshat et al., 2023). By using these theories as theoretical lenses, this research provides a comprehensive framework for exploring AI adoption in performance management.

3. Research Methodology

3.1 Research Design

Initially, the research aimed to conduct a case study involving interviews with HR managers and employees to capture a comprehensive perspective on AI adoption in performance management. However, during the initial phase of contacting organizations and experts, it became evident that no companies currently using AI in performance management were willing to participate in the study. This reflects the nascent state of AI implementation in this domain, underscoring the challenges and complexities of studying this topic at this stage. Due to this early stage, the research did not focus on any specific AI tool or technology. Instead, it provided a general overview of practical applications, maintaining a high-level perspective. The literature review adopted a similarly broad approach, highlighting the ambiguity surrounding AI tools, including how AI is adopted and its general operation. Additionally, details about the data used to train and develop these tools are often unclear, adding another layer of complexity to understanding AI applications in this field.

Consequently, the research focus shifted to the intention to adopt AI in performance management. Preliminary interviews with two employees from an organization not using AI revealed that detailed insights into specific AI tools and their impact on employees were needed. This indicated that researching employee perceptions directly was premature without more concrete implementations to discuss. Therefore, the study focused on HR professionals, aiming to gather broader insights grounded in practical experience. Including multiple companies in the study ensured a more comprehensive understanding of the diverse anticipated challenges and opportunities associated with AI adoption in performance management.

The study adopted an exploratory qualitative research design to delve deeper into the emerging field of AI adoption in performance management, specifically among knowledge workers in traditional organizational settings. The qualitative approach was particularly suited for this study as the field is being explored with scarce research and real-life implementation of performance management. It allowed for a deep understanding of complex, context-dependent dynamics crucial at the formative stages of technological adoption.

An extensive literature review was conducted as a foundational step; see Appendix A: Literature Review Methodology. This review focused on AI applications in HRM and performance management and adoption of (AI) technologies. The literature review helped frame the research questions and develop interview guides by providing a theoretical backdrop.

3.2 Participant Selection

The study targeted a diverse group of HR professionals pivotal in exploring and potentially adopting AI technologies in performance management, particularly for knowledge workers in traditional organizational settings. Given that AI adoption in performance management is still in its early stages, this selection aimed to capture diverse perspectives across the strategic, advisory, and technical dimensions of AI adoption. Including companies operating in the Netherlands ensured that the findings reflected the regional dynamics and regulations influencing AI adoption.

Participants were chosen based on their roles, expertise, and sectors to provide a comprehensive understanding of AI adoption in HRM. The diverse selection ensured a balanced representation of views from different professional angles, enriching the study's insights.

- HR Managers (7 interviewees): As primary decision-makers in HR departments, HR Managers offered crucial insights into strategic adoption efforts and organizational approaches to AI. Their involvement in performance management made their perspectives essential for understanding how AI could enhance these processes.
- HR Consultants and Advisors (5 interviewees): These experts, with experience across various businesses, provided valuable external insights and support for AI adoption. Their advisory roles enabled them to highlight broad challenges and opportunities, offering a comprehensive view of AI adoption dynamics.
- People Analytics Managers and Data Scientists (3 interviewees): As specialists in data-driven HR, these participants were essential for understanding AI's impact on analytics and decision-making. Their technical expertise ensures that the study captured the nuances of AI's practical applications in HR.

The emphasis on performance management for knowledge workers in traditional organizational settings arises from the distinct nature of their work, including job functions, performance management criteria, and evaluation processes, which are deeply embedded in existing organizational practices. Unlike job roles where performance criteria are straightforward and easily measurable, the performance of knowledge workers, including those in technology solutions and consultancy sectors, relies on more intangible metrics. Knowledge workers in these sectors contribute through cognitive activities, which require different approaches to measurement and evaluation.

Participants were selected from sectors actively engaging with AI technologies through direct implementation or consultancy services. This sectoral diversity ensured a balanced representation of both technology developers and users. In the Technology Sector, six interviewees were professionals from companies involved in technological services and product development. These participants provided perspectives on the technical and operational aspects of AI implementation. The Consultancy Sector included four interviewees from firms specializing in HR and organizational strategies, reflecting AI adoption's strategic and practical challenges. Additionally, five interviewees were selected from the Technology Solutions Consultancy Sector, comprising experts who bridge the gap between AI providers and end-users. These participants offered insights into the customization and implementation processes necessary for successful AI adoption. An overview of the participants with their anonymized ID labels is shown in Table 2.

Recognizing the nascent stage of AI in HRM, recruitment specifically targeted individuals active in LinkedIn groups dedicated to HR analytics and technology. Additionally, employees from consultancy firms advising on HR technologies and technology companies potentially utilizing AI for various business functions were included. This approach tried to ensure the inclusion of participants interested in and positioned at the forefront of AI discussions and adoptions within HR settings.

Participant ID	Role	Industry
P1	HR Advisor	Technology & Consulting
P2	HR Consultant	Consulting
P3	HR Manager	Technology & Consulting
P4	HR manager	Technology
P5	HR Manager	Technology & Consulting
P6	HR Manager	Technology
P7	HR Consultant	Consulting
P8	HR Consultant	Consulting
P9	People Analytics Data Scientist	Technology
P10	People Analytics Manager	Technology
P11	HR Manager	Technology & Consulting
P12	HR Manager	Consulting
P13	HR Manager	Technology
P14	HR Advisor	Technology
P15	People Analytics Manager	Technology & Consulting

Table 2. Participant list

The study included 15 interviewees, comprising eight women and seven men, ensuring gender balance. This approach aimed to capture gender-based perceptions towards AI in HRM, thereby enhancing the depth and inclusivity of the research insights.

3.3 Data Collection

Data was collected through semi-structured interviews. This method allowed in-depth exploration of participants' perceptions and plans regarding AI in HRM's performance management. The participants were HR managers and professionals who had expressed interest in or were actively developing and implementing AI technologies within their organizations or for their clients. These professionals were recruited through LinkedIn, professional networks, and direct emails, ensuring a purposive participant selection aligned with the research aims. In total, 180 organizations, companies, and experts were contacted to gather more information on this underexplored topic and find interview participants. This outreach effort resulted in 15 participants willing and able to do interviews, yielding a response rate of approximately 8.33%.

Interviews were scheduled via email and conducted using Microsoft Teams and, in one case, Zoom. Before each interview, an informed consent form was shared with the participant. With consent from the participant, the call was recorded and securely stored on the TU Delft drive. The researcher checked and corrected the automatic transcription via Microsoft Teams to ensure the accuracy and integrity of the data.

The interview began with a discussion on AI to standardize participants' understanding of the technology within HRM contexts, followed by the definition of AI adopted in this research. This standardization was crucial as it ensured that all participants discussed AI with similar foundational knowledge, facilitating meaningful comparisons across data. The interviews aimed to explore not just current implementations, which were rare, but predominantly the interests, expectations, and plans for future AI adoption in performance management.

The interview script was designed to guide the discussion with topics, yet it allowed participants to lead the conversation in directions they deemed relevant, see Appendix F: Interview Script English. This flexibility in the order of topics could uncover new insights that might not have been anticipated, enriching the research with unexpected perspectives and a deeper understanding of the subject matter. The interview script included a mix of open-ended questions to encourage detailed responses and specific questions to gather targeted information. Topics covered included definitions of AI, current and planned AI uses, tools/software, adoption challenges, employee perceptions, organizational impact, and strategies for enhancing AI adoption. The interview questions were crafted to probe various dimensions affecting AI adoption in performance management: technological, people, organizational, and external factors.

The interview process was deliberately iterative, designed to continue until saturation was reached—where no new themes or insights emerged from discussions. This principle ensured a comprehensive exploration of the subject matter and validated the robustness of the findings by confirming that the data adequately covered the research questions posed.

3.4 Validity and Reliability

A peer translated and reviewed interview questions to ensure alignment between the English and Dutch versions, safeguarding the clarity and consistency necessary for accurate data collection across languages. Further, the interview script was evaluated by a fellow researcher and supervisor, enhancing their relevance and alignment with the study's objectives and ensuring internal validity.

The study aimed to enhance the generalizability of its findings through strategic participant selection across various sectors and roles within HR. This diversity supported the transferability of the research findings to other contexts. However, it should be noted that it is an exploratory research with a limited participation.

Codes were defined precisely, ensuring they were clear and applicable across various data segments. This clarity led to higher reliability in classifying data and supported more decisive conclusions from the coding process.

By using multiple data sources and methods (interviews, literature review), the study enhanced the depth of understanding and corroborated findings across different evidence forms. Triangulation helped to confirm the consistency of the results obtained from different methodologies and perspectives.

A thorough description of the research design, data collection methods, and analysis processes in the research documentation enhanced transparency. It allowed other researchers to understand and evaluate the research process comprehensively.

3.5 Ethics and Data Management

Ethical considerations and data management practices were central to maintaining the integrity and confidentiality of the research process. Data management encompasses the processes involved in the collection and secure storage of research data. Given the involvement of human subjects, stringent measures were implemented to align with the standards set by TU Delft. Upon obtaining approval from the research supervisor, the researcher drafted a data management plan and an informed consent form. This plan addressed all potential concerns related to data handling and was formalized in a standard data management form. The TPM faculty's data steward was consulted to check the data management plan and informed consent form to ensure that all aspects of data handling were addressed. The revised documents, including the data management plan and the informed consent form, were reviewed and endorsed by the Human Research Ethics Committee

(HREC) at TU Delft. The consent form is included in Appendix E: Informed Consent Form for transparency and reference.

Before the interviews, participants received the informed consent form, giving them sufficient time to review the document and ask any questions. At the start of each secured video call, participant consent was explicitly reconfirmed—with a confirmation of the signed form and verbally at the beginning of the recording, ensuring dual verification of consent. All recordings and consent forms were securely stored in a TU Delft-approved Microsoft account and secured in a TU Delft drive, accessible only to the researcher.

All video recordings and identifiable data were destroyed after the research concluded to protect participant anonymity. In the research report, all references to participants used pseudo-anonymized names, ensuring their privacy.

After completing the research, each participant was sent a thank-you email with a copy of the thesis report. This approach expressed appreciation for their contribution and shared the study's findings, responding to a common request from participants during their interviews.

3.6 Data Analysis

The study employed an iterative thematic analysis methodology using ATLAS.ti, a licensed qualitative data analysis software. This software facilitated the organization of interview transcripts, systematic coding, and visualization of findings, essential for efficient data retrieval and examination.

Thematic Analysis was used to identify, analyze, and report patterns (themes) within the data, providing a detailed description of the data set. The process involved familiarizing with the data, generating initial codes, searching for themes, reviewing, and defining and naming themes.

Initially, broad thematic categories were identified and refined into more precise sub-themes through successive rounds of analysis. This iterative process allowed themes to evolve in response to accumulating data.

The analysis began with an initial coding phase, which involved closely reading the data to generate a comprehensive list of codes. Codes are words or short phrases that capture the summative essence of a data segment. These codes were then grouped into categories and further refined into themes. The process was inductive, moving from specific observations to broader generalizations.

After the initial coding, focused coding was conducted to refine and consolidate the codes into significant themes. This involved identifying patterns and relationships between codes to develop more abstract categories. ATLAS.ti's querying and networking capabilities were used extensively during this phase to trace and visualize the interconnections among themes, enhancing analytical rigor and uncovering complex patterns and relationships within the data.

Throughout this iterative process, the analysis progressed from generating numerous initial codes to a more focused set of themes. Ultimately, 75 codes were identified, organized into 17 themes, grounded in 818 data segments. This systematic approach ensured a robust and comprehensive understanding of the qualitative data, facilitating a rich and nuanced interpretation of the study findings.

4. Findings

4.1 Current Adoption of AI in Performance Management

4.1.1 Understanding of AI According to HR Professionals

The collective understanding of AI in general among HR professionals highlights a consensus that AI involves advanced algorithms and data processing capabilities. AI is recognized as a versatile tool that can assist in various tasks, from creative content generation to enhancing decision-making processes. One HR manager noted, “Actually, the first thing I think of is, of course, ChatGPT, [..] creating nice videos or photos for websites” (P5). Another consultant described AI as "anything where no human work is involved," citing examples like automated report generation (P8). Furthermore, a People Analytics Data Scientist commented, “Because now we also have a GenAI which from my perspective is different from the AI that people were talking about before ChatGPT came out, although technology-wise it's been, you know, it's a deep neural network and but there's more nuance to that” (P9). These findings indicate that the perception of AI varies slightly according to professional roles within HR, reflecting a nuanced and role-specific understanding of AI's potential and applications.

HR managers emphasize AI's advanced capabilities, particularly its deep learning and data analysis potential. They view AI as dynamic and adaptive, able to learn and evolve from the data it processes. This perspective underscores the transformative potential of AI in mimicking human decision-making processes and improving operational efficiency. Additionally, AI is perceived as having a broad scope and capable of helping in numerous ways, including content creation, which received widespread attention due to ChatGPT.

HR advisors/consultants focus on AI's practical applications, especially in automating and enhancing decision-making processes. They highlight AI's role in increasing efficiency by automating tasks that traditionally require human intervention, such as report generation and data analysis. This pragmatic view emphasizes efficiency and the broad applicability of AI in simplifying tasks and processes.

People Analytics Managers/Data Scientist offer a more technical and detailed perspective on AI. They discuss the evolving definitions of AI, contrasting historical and contemporary understandings, noting that “what was once considered AI in the 1950s and 60s differs greatly from today's understanding” (P10). This group critically assesses terms like "learning" and "experiences,” often distinguishing between simple data processing and actual cognitive functions. Their insights reflect a deep engagement with the technical aspects of AI and its implications for future developments in the field.

4.1.2 AI Adoption Level

The findings from this study indicate that the adoption of AI in performance management within the interviewed organizations is minimal. Four companies explicitly stated they do not use any tools or software for performance management, as they are still developing their systems early. AI is used primarily for generative tasks such as generating text or emails and summarizing conversations. For instance, some HR professionals use ChatGPT or an internal chatbot to write emails or plan, although they still rely on personal input to refine their outputs. Additionally, some companies restrict the use of AI tools like ChatGPT due to security concerns, as noted by P7: "We are no longer using ChatGPT at the moment because our IT department does not consider it completely safe.”

Despite the limited use of AI in performance management, AI is applied in other HR processes within some of these organizations. AI technologies are employed for tasks such as summarizing documents, finding policies, and addressing HR-related inquiries. For example, one organization uses a large language model in combination with Workday to assist with various internal processes, though its application in performance management remains uncertain. Similarly, P10 mentioned developing a model to predict turnover and an HR chatbot: "We've built a model using AI to predict turnover... Another example is that we've developed an HR chatbot using AI. This is based on OpenAI technology. I think these are the two best examples of how we're currently applying AI".

4.1.3 Future AI Integration

The insights gathered from participants reveal significant uncertainty about the future integration of AI in performance management within organizations. Participants generally expressed uncertainty or could not envision specific AI applications in this area when first asked. This indicates a lack of active research or consideration of AI's potential in performance management. This widespread uncertainty is in line with the emerging stage of AI in performance management, where its practical application is still being understood and developed. However, there is a strong curiosity and intent to explore future usage. P1 expressed this interest: "We're absolutely curious about that, and I think in the future, we will definitely use it if things come up." Participants highlighted the exploratory phase they are currently in regarding AI adoption for other processes. This uncertainty is particularly pronounced among HR managers, who accounted for 57% of comments expressing doubt or non-specificity, compared to 39% from HR advisors/consultants and only one comment from a People Analytics Manager.

The reality of adopting AI in performance management is seen with skepticism and inevitability among the participants: most participants (11 out of 15) expressed doubts about the near-term feasibility. Despite recognizing the rapid advancements in AI and its increasing adoption in various sectors, many participants express doubts about its current applicability and efficacy in performance management due to the complexity and qualitative nature of the process. As P12 remarks, AI might eventually learn to incorporate emotional and relational aspects. Still, the technology is not yet sophisticated enough: "I don't know if the technology is advanced enough yet to cover, you know, visual, emotional, and relational aspects. Maybe it will happen someday, but it’s still a remake of something existing." Additionally, P10 questioned the ethical aspect: “When you look at performance management, I find it much more difficult because then you almost get into a kind of philosophical discussion. Do you want AI to make an evaluation of a person?”.

Recruitment is perceived as a domain where AI will be integrated sooner than in performance management due to its more analytical and less qualitative nature. As P4 explains, "Recruiting is very analytical by default... Performance management has a very large qualitative element into it."

There is a consensus that AI will significantly impact the workforce and business processes in the future: “I think it’s inevitable that we’re going to use AI applications in all business processes, consciously or unconsciously. I think it will become inseparably linked to our work” (P3). Nevertheless, in what way or to what extent is still questionable, as outlined by P4: “I really think for AI to become part of an official performance management process, it's gonna take even more time. And then for it to be run 100% by AI, I think, I really don't see this happening”.

4.2 The Potential of AI Adoption for Performance Management

Through analyzing interviews, four key second-order constructs emerged: Decision Support, Personalization and Engagement, Operational Efficiency, and Strategic Enhancement. In this and the next subchapters, these second-order constructs synthesize a range of first-order constructs identified in the data (written in bold). They are presented in order of frequency, starting with the most frequently mentioned. If the number of participants that underscore the construct is 10 or higher, it will be written out; if underscored by nine or fewer participants, it will simply say "participants."

These constructs provide a comprehensive understanding of how AI could enrich current performance management practices, addressing the specific needs identified by HR professionals. ‘Decision Support’ highlights the potential of AI in enhancing decision-making processes. ‘Personalization and Engagement’ underscores the ability of AI to tailor feedback and development plans to individual employee needs and enhance employee engagement. ‘Operational Efficiency’ emphasizes that AI could streamline administrative tasks in performance management. Lastly, ‘Strategic Enhancement’ shows how AI could enable HR to take a more strategic approach by providing predictive analytics and long-term insights.

4.2.1 Decision Support

Decision support emerged as the most frequently mentioned aspect, grounded in 119 quotes. It primarily emphasizes generating performance insights (60 quotes) and improving objectivity (48 quotes)

AI's capability to analyze and synthesize large volumes of performance data provides detailed **insights into employee performance trends,** a potential unanimously acknowledged by participants. This capability is considered the most promising potential of AI in performance management, as it also enhances the objectivity of performance evaluations. One participant noted, "If somehow your emails, your information exchange between employee and some other selected group can be analyzed by AI and then quantified, I think that would play a very important role in the review process because it's quantified" (P9). Another participant highlighted AI's role in self-assessment: "Gaining insight into your own performance would certainly be a relevant option, and it would be good to have a mirror held up to you" (P11).

Many participants (11 out of 15) highlighted AI's potential to **enhance objectivity** in performance management evaluations and mitigating biases. As one participant noted, “The biggest challenge with performance management is the biases that managers have. We are hoping that we wouldn't have that with AI, so this would already be a very big value added” (P4). By biases, P4 refers to managers' subjective tendencies towards employees, influenced by personal relationships, cultural traits, race, or gender. For instance, a manager might overlook an underperforming employee’s shortcomings due to a favorable relationship or undervalue a competent employee due to personal biases. However, not all participants were clear on what bias entails. P8 noted, "You can, of course, address the bias, but you can also remove the bias. That's always the risk, isn't it, that AI can have a certain bias, but you can also remove it." This indicates that understanding bias and its implications can vary among individuals. It is clear that AI is associated with both the potential to reduce and the risk of perpetuating biases. Another participant elaborated on the objectivity AI could bring: “One of the hardest things in performance management is determining how close something is to the truth. But... if you have a dashboard with multiple data points, I think having a clear overview makes everything more objective” (P2). Additionally, AI’s capability for extensive comparisons was mentioned: “With AI, you can compare job roles across the entire country” (P7).

AI was highlighted as a valuable tool in **supporting managerial decision-making** by 11 participants. One participant remarked, "AI can support by presenting specific data that makes conversations easier for managers" (P2). Another participant elaborated, "I can imagine that as preparation for a meeting, it would be helpful for a manager to link the right sources for each individual and have AI analyze them" (P13). Furthermore, AI's capability to offer practical tips for performance reviews was noted, which could significantly enhance managerial effectiveness.

4.2.2 Personalization and Engagement

There is broad recognition that AI has the potential to enhance **communication** through content generation and improved **interaction** methods, as noted by 10 participants. While some organizations have already employed AI tools like chatbots, the potential for further improvement is considerable. Participants highlighted practical examples like job descriptions and newsletters: “Everything that we do around content generation... I think this is going to be the first phase of the implementation” (P4). Furthermore, AI can support individuals with lower educational backgrounds by refining their communication and aiding in the composition of evaluations.

AI enables managers to **focus more on employees**, reducing administrative burdens. As one participant expressed, "It's always nice to have more time to give personal attention to your employees... For me, that's the people, and I think that can only help organizations" (P5).

AI enhances **performance coaching and feedback.** As a participant noted, AI offers the potential for individualized plans: "You could develop an algorithm to determine which personality fits best with which learning method" (P7). By aligning input from both managers and employees, AI supports training needs and offers individualized career paths.

Finally, AI can customize performance management to be more **personal and flexible**, enabling dynamic adaptation to individual circumstances.

4.2.3 Operational Efficiency

AI's ability to automate routine tasks and standardize contributes to the **efficiency and automation** of processes, underscored by 12 participants. Specifically, AI's strength in combining tools and data is emphasized.

AI **reduces the time required for** performance management tasks. "If you just tell AI, 'Okay, we want to extract these points and make a summary of the most important aspects,' it would save so much time" (P8). AI could help to document information from one-on-ones efficiently.

4.2.4 Strategic Enhancement

AI could bring **broad positive organizational changes** through improved training and employee satisfaction. "If it helps with employee satisfaction, it always helps a lot. Of course, it's also good for business results" (P1). AI aids employees in reaching higher performance levels quickly: “It's like the equipping them with a very skilled coach, right? So they actually can reach a higher level very fast. This, obviously, is a gain for the company” (P9).

AI's **predictive capabilities** aid proactive decision-making and future performance planning. Participants acknowledged AI's potential in developing predictive models and its significant predictive value.

AI can aid in **strategic workforce planning** by ensuring the right people are in the right roles to meet future objectives, also due to performance insight generation. "Analyzing who the key players are within an organization... Performance management, in my view, is much more than just analyzing current performance; it's a foundation for understanding what we can achieve with the current population in the future" (P6). AI could help to bundle and analyze data for effective workforce planning.

Several sub-aspects were closely associated with each other. Managerial decision support is closely associated with performance insight generation, as the insights generated by AI facilitate managerial decision-making. Performance coaching and feedback are associated with performance insight generation, a consequence of personalization and flexibility, and have a positive organizational impact. Additionally, personalization and flexibility are associated with enhanced performance coaching, and reducing the time needed for performance management tasks is linked with more focus on employees.

Figure 2, a visualization of the potential in AI adoption per category, provides a comprehensive understanding of how AI can transform performance management practices. This figure illustrates the various categories with the sub-aspects. See Figure 6 in Appendix G: Detailed Figures from Findings for a detailed overview, including the associated links between these sub-aspects.

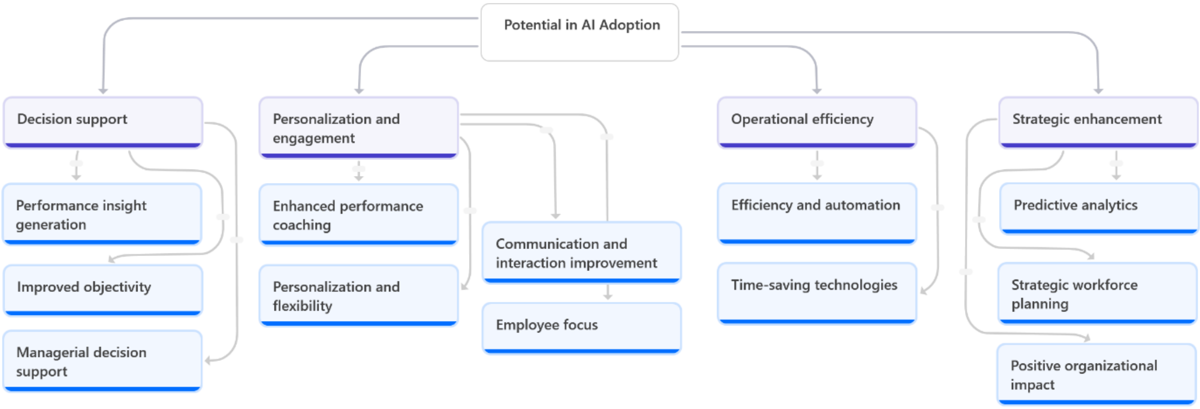

Figure 2. Potential in AI Adoption

4.3 Challenges in AI Adoption for Performance Management

The analysis of conducted interviews identified four overarching challenges in AI adoption for performance management, categorized into technology-, organization-, people-, and environment-related challenges. These categories stem from the theoretical lenses of TOP and TOE theories, which structured the interviews and guided the research. Each category consists of various sub-aspects, presented in order from most grounded in the data to least mentioned. These challenges hinder effective AI adoption and highlight the need for comprehensive strategies to address them.

4.3.1 Technology-related Challenges

The most frequently cited challenge by 14 out of 15 participants is the **complexity of evaluating non-quantifiable performance factors**. While AI can measure certain aspects of performance, there are significant doubts about its ability to capture the nuanced elements of performance, such as individual circumstances and soft skills. P10 summarized this challenge: “AI can only do that based on the available data, like emails, chat reviews, and such. That seems quite limited to me. You don’t get the full picture of the employee. For example, how people act in meetings, how well they can get others on board with ideas, their persuasive power, their way of collaborating. Someone might send a fine email, but could be a nightmare to work with. What do you do then? I don’t want an incomplete picture based on emails. So, for me, the picture is incomplete if you only look at emails, chats, and maybe physical deliverables”. HR managers mention this challenge relatively more frequently.

Participants expressed varying views on **AI's compatibility with different job functions**. While some believe that setting specific objectives for each role allows for uniform measurement, others highlighted the significant variation in AI application across different job roles and contexts. One participant noted, “Everyone has different roles, but for each role, you set a specific objective. You are measured or evaluated based on the agreement you made, and that's independent of the role.” Contradictory, another participant said, “It also depends on the type of organization. You can set KPIs, such as if you get a certain question, you have to answer it within a specific time frame. That's easy to measure. But is that applicable to every role?”.

Ensuring **data quality** poses significant challenges for effective AI functioning. Participants noted that high-quality and vast amounts of data are essential for AI's added value, which many organizations lack due to organizational size constraints. However, one participant also noted that AI could help with this, “the quality of outputs depends on the input, right? … Currently, in many spaces, the quality is not good,... but I think there's also opportunity in there because when you generate those text, maybe GenAI can already help you to improve the quality of your output, right?” (P9). People Analytics Managers/Data Scientist mention this challenge relatively more frequently.

Concerns were expressed about the current **quality of technology** of AI tools in performance management. Participants doubted whether existing technology could effectively measure performance. One participant stated, “I don't think that this technology is already there,” while another remarked, “If AI does it with 10% errors, people will focus heavily on that 10%. They'll question how a system can make such mistakes, which reflects our perception of the infallibility of these systems.” (P10).

Operational and technical challenges in **deploying AI tools** were noted, particularly the problem of tool fatigue and the scattering of data across multiple systems. A participant mentioned, “We're all a bit tool-fatigued at the moment, so when a new tool comes along, it feels like just another one.” (P2). Another added, “The downside is when you have a cacophony of tools because your data ends up being scattered everywhere.”(P6).

4.3.2 Organization-related Challenges

Organizations face difficulties in defining and standardizing **performance evaluation criteria**. Twelve out 15 participants highlight this challenge. Participants expressed concerns about the rigidity of job profiles, which may not align with companies emphasizing flexible roles and entrepreneurial activities. P3 observed, “You actually revert to a more rigid or strict job profile. That doesn't fit with many companies”. P12 added, “You need an ideal image of the person or the role, but roles are already outdated. We no longer talk about roles; we talk about the tasks someone takes on, depending on the need. So, what are you comparing it to? … We no longer do performance evaluations. Instead, we look at someone's development potential and ask the person about their ambitions and what makes them happy and energized. These are more important questions than 'how do you perform? ”. Additionally, P11 noted, “What it might do is make everything very performance-driven. When you start using AI, it's always about improving, improving, improving, which in itself isn't a bad idea. However, this can also impact the workload, performance pressure, and competition within the organization.”

Organizational structures and size can also pose a challenge, as they are closely tied to the quality of data and resource constraints. Participants noted that it is more realistic for smaller companies for humans to manage performance due to personal relationships and the direct communication possible in smaller settings. One participant remarked, “I don't notice many problems there because I personally know everyone.” Additionally, one participant mentioned that despite being a large company, the organizational structure presents challenges to adoption, with partners each managing a part of the company.

Financial and human **resource limitations** impact the feasibility of AI adoption. P1 highlighted, “It could bring us a lot, but it’s not yet really worth the amount of energy that still needs to be invested in implementing and developing it.”

Competing priorities and urgent organizational needs impact the focus and resources allocated to AI initiatives in performance management. People Analytics Managers/Data Scientist mention this challenge relatively more frequently. P7 noted, “When a budget is allocated within an organization, and they need a new technology solution, they often choose financial administration first.” P15 added, “If you ask me if I think it will happen, then no, there is no priority to look into that.”

4.3.3 People-related Challenges

Thirteen out of 15 participants highlighted the **diverse perceptions of AI adoption**, reflecting variations in age, educational background, technical expertise, and personal attitudes toward technology. Younger employees are generally viewed as more open to AI but more concerned about data privacy, while older employees, though sometimes more skeptical, may show interest in technological advancements. One participant highlighted, “Maybe it has more to do with education level than age. Lower education levels often think, 'Do we really need this?' whereas those with higher education levels say, 'Oh, cool, let's explore this and get started’” (P11). Additionally, participants worry that adopting AI may widen the gap between different groups of employees.

Employee resistance emerges as a critical challenge, explicitly mentioned by 14 participants, stemming from skepticism or fear of AI's impact on their jobs and workflows. A participant noted, “There’s a lot of skepticism. Is it fair? How can a machine know how I’m performing?” (P4). Additionally, P6 highlights that there may be less resistance to the technology itself, but “ what matters is the decision you make based on what you take from it.”. Additionally, participants noted that some people were not even interested or concerned about it; there was already resistance there.

The necessity of **personal attention** in performance management is a strong sentiment among participants, explicitly mentioned by 12 participants. AI cannot replace the nuanced, empathetic attention human managers provide. “AI might provide an initial framework by suggesting certain scenarios. However, determining the best or most appropriate scenario requires a human touch because there are factors that, in my opinion, cannot be captured solely in ones and zeros” (P12). Another participant emphasized, “The strong need for human feedback cannot be underestimated” (P11).

The lack of **understanding of AI technology**’s capabilities and limitations can pose a challenge. P2 commented, “It’s more about people not understanding what AI is than anything else.” People Analytics Managers/Data Scientist mention this challenge relatively more frequently.

The lack of **skilled personnel knowledgeable in AI technologies** poses a challenge. One participant explained, “There’s a gap between what a data scientist or someone who develops AI knows and what an HR person understands. This creates miscommunication or a lack of mutual understanding about what you’re doing and what’s possible” (P15). This gap can lead to solutions that do not meet user needs or are not effectively utilized.

4.3.4 Environment-related Challenges

The primary environment-related challenge identified by participants is the **concern surrounding privacy and surveillance**, mentioned by 12 out of 15 participants. These concerns focus on how AI systems manage personal data, user consent, and surveillance capabilities. As summarized by P11, “Do you really want a sort of Big Brother scenario where someone is constantly watching over you, monitoring the content and language of your emails?”. However, some participants noted that some employees are unconcerned about privacy issues.

Ten participants mentioned **ethical concerns**. Participants expressed apprehension about the moral implications of AI, such as bias and inequality. As explained by a participant discussing the risks of ethical breaches due to AI learning from biased data available online: "We talk about eliminating biases, right, which is a good thing. But how is this going to happen if machines are learning from what is available out there, the Internet is full of biases" (P4). Another participant explained the potential for unethical behavior facilitated by AI: "You might have wanted to act unethically, but you couldn’t because the technology wasn't there. Now, that's changed, and you have become the bottleneck. You are the moral compass " (P10). Another participant, when talking about the ethical concerns, underscored: "It really depends on too many factors, it really depends on the quality of the tooling. And how you can ensure that and what you can and cannot include. How is it measured? (P3)" This challenge was highlighted by all People Analytics Managers/Data Scientist.

Regulatory compliance was a less frequently mentioned challenge, highlighted by only three participants. These discussions centered on complying with regulations like the General Data Protection Regulation (GDPR) and other legislative requirements.

Sevel sub-aspects were closely associated with each other. Evaluating non-quantifiable performance factors presents challenges, particularly in job function-AI compatibility, performance evaluation criteria, and the human element. Performance evaluation criteria are intertwined with job function-AI compatibility and the complexity of non-quantifiable evaluations. The quality of technology and data is closely linked to available resources. Personal attention is crucial in navigating the complexity of non-quantifiable evaluations. Understanding AI technology’s capabilities and limitations can contribute to resistance and is influenced by diverse workforce perceptions. Privacy and surveillance concerns are also tied to employee resistance, ethical implications, and varying workforce perceptions. The diverse perceptions surrounding AI adoption affect employee resistance, privacy, surveillance, and understanding of AI technology. Employee resistance is often linked to privacy concerns, diverse workforce perceptions, and a lack of understanding of AI technology.

Figure 3 visualizes the anticipated challenges in AI adoption for performance management, categorized into four main areas: technology-related, organization-related, people-related, and environment-related challenges. Each overarching category comprises several sub-aspects, providing a detailed perspective on the issues that may arise within each domain. Figure 7 in Appendix G: Detailed Figures from Findings offers a more in-depth exploration, illustrating the interconnectedness between various sub-aspects.

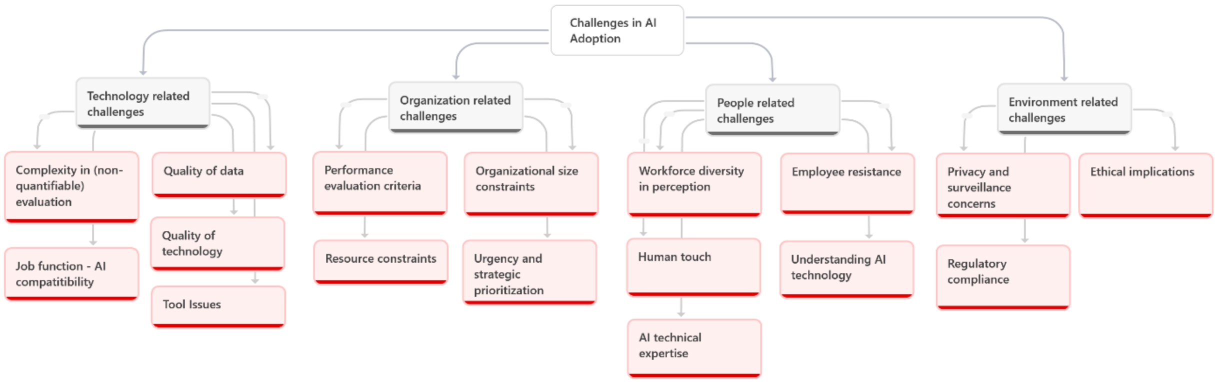

Figure 3. Challenges in AI Adoption

Lingering under many of the answers about possible problems participants give is the question of what constitutes a good employee or good performance management. The consensus is that what defines good performance varies by individual and organization. P2 shared a recent complex discussion: "Someone asked a question: I have someone who just missed their goal. But they helped Maria support her goals, and she achieved them. What do you do with that? One person says, well, they didn't achieve their goal, so they get a two instead of a three, and another says, but you helped someone with their goal, so you get a three, and another says, no, but that wasn't the question." This highlights that organizations must contemplate these nuances. P12 emphasized that added value to the team can indicate good performance: "While you can also say, yes, someone is incredibly sociable and ensures that the department stays together. Well, that is also very valuable. And then they might not deliver as much output, but if you look at it holistically, they are a super important employee."

The added value is also dependent on what a company aims for. Another participant highlighted the importance of entrepreneurship in their company when discussing good performance: "For example, at our company, we don't really have job profiles with predefined deliverables. Because we say we believe in entrepreneurship, so we find it very important that people go beyond the boundaries of their own position and take on various projects. And the looser these projects are, the less predefined and the less measurable the added or not added value is" (P3). P7 underscores that good performance management could be defined by the type of people who fit well within the company, using personality tests to create an ideal employee profile. However, this approach could lead to uniformity, which is not always desired: "You then get a sort of, almost uniformity. That all employees are compared against a golden standard AI determines for you." (P10).

In conclusion, as P15 summarizes: "Ultimately, the hardest thing about performance management is determining what performance is. And as long as that is not clear or unambiguous, you get nowhere. But it doesn't matter if you use AI, very simple data, or just a straightforward KPI. So there is a big stumbling block."

4.4 Strategies for AI Adoption for Performance Management

The analysis of interviews identified four key strategies for AI adoption in performance management, categorized into technology-, organization-, people-, and environment-related strategies. These categories reflect the theoretical lenses of TOP and TOE theories, which guided the research and structured the interviews. While the same four themes were used to categorize challenges, the findings for strategies emerged from different parts of the interviews, making them distinct. This distinction is essential to understanding the comprehensive approach for successful AI adoption.

4.4.1 Technology-related Strategies

The most frequently mentioned strategy among all groups, discussed by 11 out of 15 participants, involves using **AI as a complementary tool** to support human capabilities rather than replace them. P3 emphasized, "Given our current situation, AI input should always be supportive or advisory to the evaluator." Similarly, P7 noted the importance of a human-AI combination, stating, "If it's a combination of human and AI, and it can be well explained that it’s used as a basis, I think it will be beneficial."

Nine participants highlighted the need to assess AI's technological, financial, and strategic impacts strategically. P15 expressed skepticism about AI’s added value: "And most things they have there, they say, 'We can look at that in another way.”

Conducting small-scale implementations as **pilot testing** before a wider rollout was identified by 10 participants as a critical step. This strategy was considered essential to evaluate the functionality and impact of AI solutions within the organization. Additionally, ongoing **technical support and validation** were deemed necessary to ensure the reliability and efficiency of AI tools.

4.4.2 Organization-related Strategies

Thirteen participants emphasized the importance of **clear and consistent communication** to achieve alignment and understanding, highlighted by P4 as the need to "over-communicate it throughout the way."

Involving stakeholders and employees in the AI adoption process was a key strategy mentioned by participants. For example, P7 advocated for early involvement: "So, I would personally involve people right away. Let's explore the possibilities of AI and what AI performance management could mean for us, and we will inform them transparently about it”.

Incorporating employee **feedback and evaluating** were seen as vital for successful adoption. The need for "success stories” was mentioned by P4, while P6 noted, "The most important thing is to convey that your input is important and that we will do things with your input. ..".

Aligning organizational culture with AI adoption was considered crucial for enhancing acceptance and efficacy. As remarked by P11, "People also create culture themselves. But it's also determined by all the, well, artifacts, as we call them, and AI would be a part of that."

Enhancing **transparency** in organizational processes was highlighted as a way to build trust among stakeholders, promoting visibility into operations and decisions. Additionally, four participants mentioned leadership involvement. P4 discussed the necessity of "getting buy-in from leadership," while P11 emphasized avoiding a top-down approach.

4.4.3 People-related Strategies

Thirteen participants emphasized the need to **highlight individual benefits** to increase acceptance. P2 stated, "The most important thing, I think, with implementing a tool like this is: what does it bring me? If you can answer that question for everyone you speak to, you'll get a long way."

Phased roll-outs were deemed essential for easing the adoption for people, with 12 participants highlighting this approach. P4 advised to "take it one step at a time." At the same time, P7 noted, "So, if the implementation lead time is one or maybe even two years and you keep people regularly updated, I think it will gradually become embedded, and people will get used to it."

Managing and mitigating resistance from employees was seen as a critical strategy. P15 highlighted the potential for resistance: "There is also a group that can put up quite a resistance. If you don't handle it well, they can mobilize the group that thinks 'whatever.'"

Ensuring that AI adoption does not diminish human interaction was essential for **preserving personal contact**. As stressed by P8: "I think there always needs to be a human touch." HR managers mention this strategy relatively more often.

Enhancing employees' skills and knowledge through **education and training** programs was identified as a necessary strategy. P4 summarized this: “Educating the company, the employees, the managers... I think it will be a challenge, like maybe having the right degree of communication and the right degree of education.”

4.4.4 Environment-related Strategies

Five participants mentioned the importance of **security measures and access controls**. P6 suggested creating a data warehouse: " The solution for that, if I may be honest, is to create a data warehouse. It's essentially a general data warehouse where all that data is centralized, and the tools will extract data from there and input it back into it… The tools have access to it, but if you log in and don't have the rights, then you won't have access to that specific data."

Five participants mentioned the need to address the ethical implications and privacy concerns. As emphasized by P10: "There must be a lot of attention to privacy, risk, and ethics in this."

The strategies for AI adoption in performance management are organized into a framework that delineates distinct phases of AI integration within HRM. This framework is structured based on analysis of the transcripts to provide a clear pathway for organizations to follow, ensuring a systematic and effective adoption of AI technologies. The framework phases are inspired by the works of Prikshat (2023) and Fenwick (2024), whose models converge synergistically, although derived from different perspectives, particularly during the initial stages of AI adoption. Fenwick's (2024) technocratic phase, which addresses technical, human, and ethical concerns of AI-HRM use cases, incorporates two critical phases by Prikshat (2023). As defined by Prikshat (2023), the initiation stage emphasizes raising awareness and evaluating the potential benefits of AI in HRM. During this stage, organizations focus on understanding the various AI technologies available, their potential impact on HR processes, and the benefits they can bring. This phase involves organization-related strategies such as leadership involvement, stakeholder/employee engagement, and strategic communication. Additionally, people-related strategies like maintaining a human touch and highlighting personal benefits, alongside technology-related strategies such as pilot testing and strategic evaluation, play crucial roles.

Following the initiation stage, organizations transition into the adoption stage. This phase is critical for assessing organizational needs, the capabilities of AI technology, and the availability of necessary resources. During this stage, organizations gain a deeper understanding of the specific functionalities of AI that can be leveraged for HR tasks, ensuring these technologies align well with organizational goals and existing processes. The adoption phase includes environment-related strategies focusing on data security and access control and mitigating ethics and privacy concerns. Furthermore, organization-related strategies during the adoption phase involve cultural alignment, evaluation and feedback, and transparency. People-related strategies encompass phased implementation, resistance management, and comprehensive training and development programs to ensure smooth integration and user acceptance. Lastly, technology-related strategies include AI augmentation, where AI enhances but does not replace human tasks, and ongoing technology support and validation to address any issues promptly.

Figure 4 visualizes strategies for AI adoption in performance management, categorized into technology-, organization-, people-, and environment-related challenges. Each category contains various sub-aspects. The strategies are presented across two stages: the initiation phase and the adoption phase. See Figure 8 in Appendix G: Detailed Figures from Findings for a more detailed overview.

To show the overlap between the categories and provide a clearer understanding of the relationship between challenges and strategies, a Sankey diagram is included in Appendix G: Detailed Figures from Findings, see Figure 9. This visual representation highlights the co-occurrence of challenges and strategies between the technology-, organization-, people- and environment-related aspects, helping to clarify their interconnectedness.

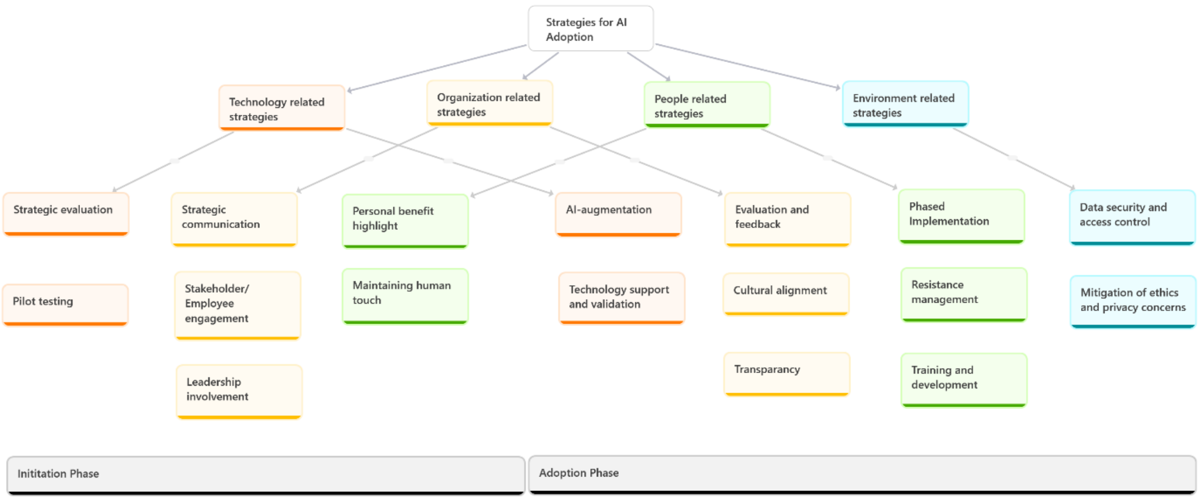

Figure 4. Strategies for AI Adoption in Phases

5. Discussion

5.1 Discussion of Research Findings

This thesis explored the adoption of artificial intelligence (AI) in performance management for knowledge workers in traditional organizational settings, aiming to understand the diverse anticipated opportunities, challenges, and strategies associated with AI adoption in this domain. From the outset, the study faced a significant challenge: finding companies actively using AI in performance management that were willing to participate in the study. This difficulty reflects the nascent state of AI adoption in performance management, emphasizing the topic's complexity and secrecy. The hype surrounding AI and its sensitive application in human-centric areas makes it a challenging subject to study. Despite these obstacles, the study persevered, focusing on what was feasible. Due to this early stage, the research did not focus on any specific AI tool or technology but provided a general overview of practical applications. The literature review adopted a similarly broad approach, highlighting the ambiguity surrounding AI tools, including how AI is adopted and its general operation. Additionally, details about the data used to train and develop these tools are often unclear, complicating the understanding of AI applications in this field.

The research findings indicate that the successful adoption of AI in performance management requires a comprehensive and multifaceted approach, addressing several key factors: technological, organizational, people, and environmental aspects. Successful adoption requires a nuanced understanding of AI's capabilities and limitations and effective strategies to overcome identified challenges. This discussion shows why and how AI could be adopted to enhance performance management practices.

Participants generally expressed uncertainty regarding specific AI applications in performance management, highlighting a lack of active research or practical consideration of AI's potential in this domain. This aligns with the emerging stage of AI adoption in performance management, where its practical applications are still being explored and understood. Despite this uncertainty, there is a notable curiosity and intent to explore AI's future usage.

The study reveals that the current adoption status of AI in performance management within companies operating in the Netherlands is minimal. The limited usage observed is predominantly related to generative AI tools such as ChatGPT or internal chatbots, primarily for generating text, emails, and summarizing conversations. This minimal adoption aligns with the Gartner Hype Cycle, which places generative AI at the "peak of inflated expectations" (Gartner, 2023). This stage is characterized by significant attention and investment, though AI's practical and sustained integration in performance management remains to be seen in the coming years.

The current opportunities organizations anticipate for enhancing performance management through AI adoption are multifaceted and reflect optimism and skepticism. AI's potential to address current challenges and needs in performance management is primarily seen in decision support, personalization and engagement, operational efficiency, and strategic enhancement. In decision support, AI could analyze vast amounts of performance data to generate detailed insights, enhancing the objectivity of evaluations and supporting more informed managerial decisions. AI could enable more personalization and engagement by tailoring feedback and development plans to each employee's unique needs, fostering a more engaging and supportive work environment. AI-driven chatbots and virtual assistants could facilitate continuous communication and motivation. Automation of routine tasks through AI could significantly improve operational efficiency by streamlining administrative processes such as scheduling reviews, tracking performance metrics, and generating reports. This reduces the time and effort required from HR professionals, allowing them to focus more on strategic activities. Finally, AI's predictive analytics capabilities enable strategic enhancement by providing long-term insights, helping organizations plan for future workforce needs and develop proactive talent management strategies. Organizations see the potential for AI to enrich performance management into more dynamic, data-driven, and employee-centric processes. As AI technologies evolve, their ability to enrich performance management may increase, potentially leading to improved decision-making, higher employee engagement, greater operational efficiency, and enhanced strategic planning.

Participants expressed curiosity about the technology's ability to enhance performance measurement, particularly in quantifying metrics, but also doubted if AI is advanced enough to add substantial value in capturing the full spectrum of employee performance. There was consensus that AI could effectively measure quantitative aspects. However, concerns remained about its capability to assess non-quantitative performance dimensions, such as competencies and skills, which are increasingly prioritized over rigid results and outcomes. This shift towards valuing competencies aligns with the findings of Tambe et al. (2019), who questioned the measurability of a 'good employee' regarding metrics and digital traceability. The evolving nature of performance management, moving away from traditional metrics, suggests a potentially limited future for AI unless it adapts to these broader evaluative needs.

To improve current performance management practices, AI could be utilized to provide more personalized feedback and development plans, cater to individual learning needs, and ensure continuous engagement through AI-driven chatbots and virtual assistants. Furthermore, AI can support decision-making by analyzing performance data to provide detailed insights and predictive analytics. However, to fully realize these benefits, more research is needed to understand AI's impact on performance management comprehensively. This is rooted in minimal experience and usage, without clear testing and proof of added value.

Moreover, HR professionals raised ethical and practical concerns about focusing on performance measurement, noting the potential negative consequences of heightened performance pressure and competition. This sentiment mirrors the stages in the Gartner Hype Cycle, where technologies like continuous employee performance management and machine learning in HR are in the "trough of disillusionment" phase (Gartner, 2023). Early implementations have often failed to meet expectations, leading to a reevaluation of their effectiveness and a cautious outlook on their future applications. This period of disillusionment is expected to last 2-5 years before these technologies potentially emerge stronger with more realistic applications and benefits.

The findings from this study reveal significant challenges in adopting AI for performance management, particularly concerning data quality and the criteria for performance evaluation. Participants consistently identified these areas as critical obstacles, yet they lacked clear strategies to address them. This aligns with existing literature, which identifies these areas as problematic in the context of AI adoption in HRM.

One of the most pervasive issues highlighted by participants is the difficulty in defining what constitutes good performance. This challenge extends beyond AI adoption and is fundamental to performance management. For instance, the dilemma shared by one participant about an employee who missed their personal goals but significantly contributed to a colleague's success underscores the nuanced nature of performance evaluations. This complexity is further emphasized by the notion that the social contributions of an employee, such as fostering team cohesion, are invaluable yet difficult to measure. These insights reflect a broader consensus that the criteria for evaluating performance are highly contextual, varying significantly across individuals and organizational cultures. This variability complicates the implementation of standardized (AI) systems, which rely on quantifiable metrics to function effectively. Tambe et al. (2019) highlight the difficulty of defining employee performance due to job role variability and biased performance appraisals. Additionally, Pan and Froese (2023) note that AI's limitations in capturing qualitative aspects like moral standards and emotional intelligence are essential for comprehensive performance evaluations. Similarly, the literature emphasizes the criticality of high-quality data for accurate AI outputs in HRM. Chowdhury et al. (2023) and Kellogg et al. (2020) emphasize the challenges in data verification and the risks of biased decision-making from small datasets. Thus, the findings resonate with these established perspectives, underscoring that these are significant challenges in AI adoption in performance management, without a clear-cut strategy for mitigation.

In reflecting on these findings, it becomes evident that many challenges attributed to AI adoption in performance management are, in fact, longstanding issues within performance management itself. The subjective nature of performance evaluations and the variability in performance criteria across different contexts pose significant hurdles, whether human managers or AI systems conduct assessments. Thus, while AI has the potential to offer more data-driven insights, it does not inherently resolve these fundamental challenges.

Employee resistance emerged as a significant challenge in AI adoption for performance management anticipated by HR professionals. This resistance aligns with Pan and Froese (2023), who emphasize the need for comprehensive integration strategies and training supported by a culture of open-mindedness for successful implementation. This study confirms that addressing employee resistance is critical, echoing Tambe et al. (2019) and Singh and Pandey (2024), who identify employee fear of lack of control as a significant barrier to AI adoption. Interestingly, this study reveals that resistance to using AI in performance management does not necessarily equate to resistance to the AI technology itself but rather to the consequences tied to the technology and data used. People are more concerned about how AI-driven evaluations might impact their salaries, promotions, and performance assessments, preferring human judgment over algorithmic decisions.

Additionally, AI is not perceived as fundamentally different from other technologies, and if AI can assist in their learning and development, people are generally open to its implementation. Moreover, diverse perceptions of AI adoption among the workforce present an additional layer of complexity, as this research shows great anticipated variation in perceptions based on age, educational background, technical expertise, and personal attitudes toward technology. Additionally, this study contradicts the findings by Tambe et al. (2019) and Singh and Pandey (2024) in AI adoption in HRM, as AI adoption in performance management does not seem to lead to fear of job loss, at least among HR professionals. Furthermore, involving employees early in the AI adoption process and addressing their fears is essential for fostering positive perceptions and ensuring successful adoption in performance management. The literature states that positive initial perceptions and early involvement are crucial for successful AI integration in HRM, leading to increased satisfaction and performance, which this study also supports for AI adoption in performance management (Charlwood & Guenole, 2022; Den Hartog et al., 2013; Leicht-Deobald et al., 2019; Tambe et al., 2019; Vrontis et al., 2022). This study corroborates that strategies addressing employee resistance are among the three TOP categories: technology, organization, and people. These strategies must be all-encompassing and intertwined across these domains during AI's initiation and adoption phases.

The paradoxical nature of AI's objectivity in performance management presents benefits and challenges. While AI can potentially reduce biases, it can also perpetuate them if the underlying data is flawed. This aligns with the divergent views in the literature on algorithmic objectivity (Bankins et al., 2024; Basnet, 2024; Chowdhury et al., 2023; Langer & Landers, 2021; Tambe et al., 2019). HR professionals in this study acknowledge that biases are inherent in human performance management, influenced by personal relationships, cultural traits, race, or gender. There is a varied understanding of bias among HR professionals. Some see AI as a tool to eliminate bias, while others worry about AI inheriting biases from flawed and historical data. Ethical concerns about AI learning from biased (online) data were prevalent, reflecting a general association of AI with bias. The literature review shows that AI applications in performance management use internal and third-party data, but transparency on AI integration and data sources is often lacking. These findings underscore the importance of high-quality data and continuous evaluation to address biases and ensure ethical AI use in performance management.

This research reinforces the existing literature on AI adoption in HRM to also apply to performance management, highlighting several critical factors: dynamics of social exchange (Tambe et al., 2019), technology skills of HR employees (Malik et al., 2022; Prikshat et al., 2023), the degree of human involvement (Bankins et al., 2024; Chowdhury et al., 2023; Fenwick et al., 2024), individual characteristics (Bankins et al., 2024; Makarius et al., 2020), and support from AI technology vendors (Pillai & Sivathanu, 2020). Support from top management, often cited as crucial in the literature (Bankins et al., 2024; Prikshat et al., 2023), was not that much emphasized by the participants, suggesting that top management support might not be as critical at the current phase of AI adoption in performance management. Leadership involvement included 'getting buy-in' from leadership and avoiding a top-down approach. Additionally, as mentioned in the HRM literature (Deloitte, 2017), competitive pressure did not emerge as a significant factor in this study. This suggests that AI adoption in performance management is not yet perceived as a competitive necessity. However, an indirect link to competitive pressure was observed during the data collection phase. Some potential participants from companies that were adopting AI in HRM could not sign the informed consent forms or provide detailed information due to company policies. This suggests that competitive concerns and the need to maintain confidentiality might influence the ability to freely discuss AI adoption in performance management.

Despite the potential benefits, the study revealed that the business case for AI in performance management is not yet compelling for many organizations. Performance management challenges, although present, did not significantly impact organizational performance to warrant immediate AI investments. This differs from other HR processes like recruitment or employee query handling through chatbots, which are seen as more pressing areas for technological enhancement.

The analysis revealed minimal differences across the three role groups of participants, suggesting a shared understanding of AI adoption challenges and strategies across various roles. People analytics managers/data scientist frequently highlighted ethical implications, urgency and strategic prioritization, understanding AI technology, and data quality issues. They mentioned the importance of understanding AI technology and the challenge of skilled personnel more frequently, attributing it to a lack of education and anticipating employee resistance. This perspective may reflect their narrow view, as experts often see their field as highly sophisticated and complex, potentially overlooking significant issues seen by others. However, they also frequently highlighted ethical implications, urgency, and strategic prioritization, showing a realistic view by underlining their field's ethical concerns and prioritization challenges. On the other hand, HR managers emphasized the importance of maintaining a human touch and noted the complexity of evaluating non-quantifiable aspects as a significant challenge. Notably, the view of AI as a complementary tool was uniformly mentioned across all groups, indicating a shared recognition of AI's supportive role in enhancing performance management.

The interviews underscore the interconnected nature of performance management with other HRM processes, such as employee turnover, compensation management, learning and development, and talent management. This realization, which practitioners increasingly recognize, underlines the importance of adopting a holistic approach to AI implementation. Integrating AI tools across these interconnected areas, rather than isolating them to performance management, is essential for achieving effective results.

AI does show promise in performance management by automating routine tasks, such as preparing conversations, writing performance reviews, and generating personal summaries from various data sources. These tasks are time-consuming and often managed with basic tools like Excel sheets. However, one major issue is the lack of specialized performance management tools within many organizations, which raises the question of whether standard technology solutions can suffice or if AI is necessary for meaningful improvements.

By addressing these concerns and implementing strategic measures, adopting AI in performance management could be both successful and beneficial, enhancing current performance management practices.

5.2 Theoretical Implications

The theoretical implications of this research offer significant new insights into AI's application in performance management. While existing literature has primarily focused on broader HRM aspects or specific areas such as recruitment and selection, this study advances the understanding of AI's role in performance management. The findings reveal that despite optimistic expectations, significant challenges persist in the early stages of AI adoption in performance management, indicating the need for further research before widespread implementation becomes feasible. This research critically examines the high expectations and potential in the literature, highlighting that these theoretical promises do not necessarily align with the current reality.

In this research, the TOP (Technology, Organization, and People) and TOE (Technology, Organization, and Environment) theories feature as theoretical lenses to guide the research process. These theories structured the interviews and shaped the research direction, providing a comprehensive perspective on the interplay between technology-, organizational-, people- and environmental factors. Reflecting on this, these theories guided the researcher's perspective, influencing the research direction and the interpretation of findings.

5.3 Practical Implications

Given the nascent stage of AI adoption in performance management and its limited use and associated uncertainties, AI adoption should be encouraged cautiously. Conducting a strategic assessment to determine whether AI provides added value over existing technologies is essential. Before AI can effectively aid in performance management, it is crucial to resolve performance management-related issues. This involves a detailed analysis of organizational issues, performance management goals, and the specific needs AI is expected to meet.

While AI offers data-driven insights, it does not inherently resolve the fundamental challenges of performance management, such as the subjective nature of performance evaluations and variability in performance criteria across different contexts. Therefore, organizations should develop hybrid models that combine AI's analytical capabilities with human judgment to ensure the multifaceted nature of employee performance is accurately captured and evaluated. Before moving to advanced technologies, organizations should clearly define their desired performance criteria and what constitutes good performance management across different contexts. Only with a clear understanding of these aspects can AI be effectively integrated to enhance performance management practices.

Furthermore, there is a risk of a self-fulfilling prophecy if companies believe AI is not yet advanced enough and, therefore, do not invest in its development. This lack of investment can stifle progress, leading to slower advancements in AI technology and reinforcing the belief that AI is not sufficiently developed to be adopted in performance management.

In traditional organizational settings, evaluating the performance of knowledge workers—who contribute through cognitive activities—relies on intangible metrics and requires different measurement approaches compared to roles with easily measurable criteria. Currently, it is unclear if AI can significantly enhance performance management for knowledge workers due to the complexity of their contributions. Therefore, organizations should first investigate the use of AI in roles with more straightforward and measurable criteria. This approach allows for establishing a proof of concept and refining AI systems before applying them to more complex roles, including knowledge workers.

Organizations engaging with AI technologies through direct implementation or consultancy services should follow market trends and client demands. By assessing potential benefits and feasibility through client-focused AI applications, companies can gain valuable external validation. This validation can serve as a foundation for internal adoption in performance management, ensuring that the technology aligns with the organization's structure, size, resources, and priorities.

To ensure AI adoption is successful, organizations must build a strong foundation. AI adoption requires a holistic approach that includes technological, organizational, human, and environmental considerations. Organizations interested in exploring AI should leverage the combined expertise of HR professionals, data scientists, and ethicists. A comprehensive evaluation of specific needs, data quality, and performance criteria is essential before moving to advanced AI technologies. Robust data management practices are crucial to ensure the reliability and effectiveness of AI applications. This includes improving data collection, integration, and analysis processes to build a solid infrastructure that supports AI-driven decision-making. A phased implementation approach is recommended, starting with pilot projects involving enthusiastic employees. This phased approach allows for cultural alignment, practical evaluation, and iterative feedback, ensuring smooth integration and higher acceptance rates.

AI should assist HR managers by generating insights and recommendations rather than making autonomous decisions. Maintaining a balance between technological efficiency and human judgment is crucial to avoid over-reliance on AI and address ethical considerations. Additionally, companies should train and develop their human capital by equipping employees with the skills and support needed for smooth integration and user acceptance.

Organizations must address data security, privacy, and ethical concerns associated with AI deployment. These steps help mitigate risks and ensure that AI aligns with organizational values and regulatory standards. Additionally, insights from this research can guide public policy on AI's ethical and fair use in the workplace, fostering a fair and secure AI landscape.

5.4 Limitations and Future Research

5.4.1 Research Limitations

This study encountered several limitations stemming primarily from the nascent stage of AI in performance management, both in literature and real-world applications. At the outset, various research groups, field experts, and organizations such as TNO and the AI Coalition were contacted. It became apparent that few were focused on AI in performance management, highlighting the early development phase of this field. The existing literature predominantly covers broader HRM or other domains rather than focusing specifically on AI in performance management. Moreover, no organizations currently using AI in performance management were identified and willing to participate, limiting the study to exploring potential applications, anticipated challenges, and strategies rather than real-life experiences. The participants often had unclear or undeveloped perceptions of what AI could mean for performance management, further emphasizing the exploratory nature of the research.

The study's focus on AI tools or technologies was broad, as no specific tools were researched in detail. This may have limited the findings, as perceptions and opinions about AI can vary significantly depending on the tool or technology. Additionally, while the organizations were categorized into broad sectors, more specific sector categorization could have enhanced the generalizability of the findings by allowing for better comparisons within and between sectors.

Initially, the research aimed also to include employees' perceptions of AI in performance management. However, due to the lack of organizations using AI in this context and after interviewing two employees from an organization that did not use AI in performance management, it was concluded that it was premature to research employee perceptions directly. Detailed information about how specific AI tools would work and impact employees was lacking. Therefore, the study pivoted to interviews with HR professionals, providing insights more grounded in experience. They discussed the employees' perspectives from a second-line view rather than direct experience. It should be noted that relying on HR professionals to represent employees' perspectives introduces a degree of indirectness. While HR professionals can anticipate what employees might say, this approach risks a one-sided and more managerial view, potentially overlooking the authentic voice of the employees themselves.

Methodologically, the study relied on qualitative interviews with limited participants, which may not fully capture the diverse perspectives and experiences across different organizations and industries. The analysis was conducted by a single researcher, introducing potential bias in coding, categorizing, and transcribing data. Participant responses may also be influenced by social desirability bias, particularly when discussing speculative topics like the future use of AI in performance management. This limitation was evident as participants' initial uncertainty about AI may have been shaped by the course of the interview. Additionally, while the Gartner Hype Cycle was used to frame the context of technological maturity, it is important to note that it serves as a practical tool rather than a scientifically rigorous framework. This may result in a simplified view of the stages of technology evolution, which could limit the analytical depth needed for scholarly research.

5.4.2 Future Research

Future research in AI-driven performance management should concentrate on organizations actively adopting AI in performance management or those already utilizing it to assess whether the anticipated potentials, challenges, and strategies identified in this study hold in practice. As time progresses, more companies are expected to engage in this field. Researchers could benefit from pursuing case studies within companies actively using AI in performance management. This could be facilitated by securing internships or collaborating with these companies early in the research process. Additionally, reaching out to companies developing AI tools for performance management could provide opportunities to work together and conduct an in-depth study of these tools within organizational contexts.

Investigating employee perceptions directly in companies that use specific AI tools for performance management is essential. Comparing these perceptions with those of HR professionals can reveal discrepancies and commonalities, shedding light on the factors that shape these views. This approach ensures the findings are grounded in direct employee experience, providing a more comprehensive and two-sided understanding. Longitudinal studies tracking the adoption and impact of AI over time would be particularly valuable, as they can provide insights into the evolution of AI's effectiveness and the long-term viability of best practices identified.

Focusing on a specific AI technology or tool enables a detailed examination of its functionalities and impacts. Conducting scenario-based research involving HR professionals and employees with this tool can provide direct, detailed insights into their experiences and perceptions.

Future research should also delve into the application of AI across different job functions of knowledge workers, such as consultants and engineers, to understand the variability in performance management practices. Some participants highlighted the significant differences in how AI can be applied to various job roles, suggesting that tailored approaches might be necessary. Selecting companies from particular sectors enhances the accuracy of comparisons and generalizations across industries, ensuring that the findings are relevant and applicable.

Ethical considerations and potential biases in AI systems emerged as critical issues during this study. Although these were not the primary focus of the current research, they represent important areas for future exploration. As the interviews and research were conducted at a high level, participants often used the term "bias" to describe decisions based on historical data. Future research should investigate these ethical considerations and AI systems' specific biases to understand and mitigate their impact. Examining AI in performance management through an ethical lens can provide valuable perspectives on what should be ethically acceptable and desirable beyond the technological possibilities.

Further studies should aim to determine whether the relationships between challenges and strategies identified in this research are merely associative, causal, or coincidental. Furthermore, future researchers could use this framework to conduct quantitative analyses, extending the research to examine broader trends and statistically significant patterns. This would complement the qualitative insights with quantitative data, providing a more comprehensive understanding of AI-driven performance management.

6. Conclusion

This study explored the adoption of artificial intelligence (AI) in performance management for knowledge workers in traditional organizational settings. The research question, "How can AI be effectively adopted into performance management practices?" guided the exploration of the current adoption status, anticipated opportunities, challenges, and strategies for AI adoption in performance management. No companies using AI in performance management agreed to participate. Therefore, insights were gathered through interviews with HR professionals, indirectly representing employees.

The minimal current AI adoption within companies operating in the Netherlands, in sectors engaging with AI technologies through direct implementation or consultancy services, mainly involves generative AI tools like ChatGPT. AI's potential to address current needs in performance management includes enhanced decision support, personalization and engagement, operational efficiency, and strategic enhancement. However, its ability to comprehensively measure knowledge worker performance remains uncertain due to the complexity of their contributions, with objectivity seen as both a benefit and a challenge. Key challenges identified include technology-, organization-, people-, and environment-related aspects. The primary challenge revolves around AI's capability to assess non-quantitative performance dimensions, such as competencies and skills. Additionally, workforce diversity in perceptions and employee resistance emerged as significant challenges. Data quality and performance evaluation criteria were acknowledged as substantial obstacles, with no clear strategies yet to address these issues.

This research significantly bridges the gap in the existing literature on AI in performance management, expanding the theoretical understanding of AI's nascent role in performance management within HRM. Despite optimistic expectations, challenges persist in the early stages of AI adoption in performance management. Practically, it underscores the necessity of a well-rounded strategy that integrates technological, organizational, human, and environmental factors. Organizations must conduct thorough strategic assessments to identify AI's value-add and implement robust data management practices to support reliable AI applications. This research provides an overview of AI adoption in performance management, guiding managers to critically examine the current state of technology and its applicability in their organization. Ultimately, AI should serve as an assistive tool for HR managers, balancing technological efficiency with human oversight to foster ethical and effective performance management, particularly in complex roles like those of knowledge workers.

Conducting this study underscored the complexity of adopting AI. While AI can potentially transform performance management, its successful adoption requires careful consideration. Many challenges attributed to AI adoption in performance management are longstanding issues within performance management itself. The subjective nature of performance management and the variability in performance criteria across different contexts pose significant hurdles. While AI offers data-driven insights, it does not inherently resolve these fundamental challenges. The findings indicate that further research is needed before widespread AI implementation becomes feasible, suggesting that many organizations may not be ready for AI adoption in the near future. However, by addressing the identified challenges and leveraging AI's potential benefits, organizations can begin to lay the groundwork for more effective and sustainable AI adoption in the future. This study has deepened the understanding of the intricate balance between leveraging AI capabilities and maintaining human oversight, ensuring that technology enhances, rather than replaces, human judgment and interaction in performance management.

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Appendix

Appendix A: Literature Review Methodology

The literature review aimed at exploring the role of Artificial Intelligence (AI) in Human Resource Management (HRM) and its impact on performance management was conducted using a multi-faceted search strategy. The method incorporated various databases and search techniques to examine the subject comprehensively.

The primary stage involved querying significant databases, including Web of Science and Scopus, using initial search terms such as "Artificial Intelligence," "HRM," and "Performance Management," along with related terms. Despite this broad approach yielding limited results initially, the focus was refined to investigate "AI in HRM specifically." Additional terms like "Implementation" and "Adoption" were introduced to enrich the scope, aiming to capture literature detailing the adoption phase of AI technologies within HRM contexts.

Search results were filtered by publication year and citation count to prioritize recent and influential studies. Given the sparse findings on AI-specific performance management, the strategy was broadened to include conference papers and grey literature, enhancing the depth of research materials. A more targeted search was conducted via Google Scholar to delve deeper into specific AI technologies utilized in HRM and to gauge professionals' and employees' perceptions regarding these advancements.

The selection of relevant literature involved a detailed screening process. Titles and abstracts were first reviewed to determine their relevance. This was followed by an examination of publication dates and citation counts to ensure the inclusion of seminal and contemporary studies. The snowball sampling technique was also employed; references within selected articles and subsequent citations were scrutinized to uncover additional pertinent sources. This iterative process helped identify direct and peripheral studies on AI in HRM.

The inclusion criteria were rigorously applied, focusing on articles explicitly discussing AI applications in HRM and their effects on performance management. Due to the initial scarcity of articles directly linking AI with performance management in HRM, broader HRM articles that briefly mentioned performance aspects were also considered. This approach gave a more holistic view of the topic, incorporating focused and tangential insights. Articles were again selected based on relevance to the research questions and their contribution to understanding AI’s role in HRM.

The literature review was structured to maximize coverage and relevance, utilizing multiple databases and a systematic approach to article selection. This methodology ensured a thorough exploration of the adoption of AI technologies in HRM, particularly their influence on performance management.

Appendix B: AI Technologies in HRM

Adopting Artificial Intelligence (AI) technologies in Human Resource Management (HRM) can revolutionize the field, offering new capabilities for managing and understanding workforce dynamics. AI encompasses a range of sub-disciplines, including Machine Learning (ML), Artificial Neural Networks (ANN), Deep Learning (DL), Natural Language Processing (NLP), and Cognitive Computing (CC).

- Machine Learning (ML) is employed to automate and improve learning from data without explicit programming. In HRM, ML aids in candidate tracking, predicting employee turnover and job success, thereby enhancing decision-making processes regarding recruitment and retention (Garg et al., 2022; Rodgers et al., 2023).

  Machine learning is an AI technology that enables systems to learn and improve from experience without being explicitly programmed (Palos-Sánchez et al., 2022; Qamar et al., 2021). It involves training algorithms on a subset of relevant data to create models that predict outcomes (Tambe et al., 2019). Standard techniques, such as logistic regression and support vector machines, analyze statistical correlations among variables to infer outcomes and can be used in HR settings (Qamar et al., 2021). In recruitment and retention, ML algorithms excel in analyzing large volumes of applicant data to predict job success and employee turnover. This predictive capability allows HR professionals to make more informed decisions, enhancing the effectiveness of recruitment strategies and reducing turnover rates (Garg et al., 2022; Rodgers et al., 2023). For example, logistic regression models predict binary outcomes such as pass/fail or accept/reject decisions during hiring (Qamar et al., 2021).

- Artificial Neural Networks (ANN), with their structure mimicking the human brain's neural networks, facilitate forecasting recruiting demands and talent selection, offering a more objective approach to managing HR needs (Huang et al., 2001).

  The structure of an ANN includes processing elements, layers, and networks that simulate the learning processes of the human brain (Huang et al., 2001). This capability allows ANNs to perform complex functions such as prediction, classification, and pattern recognition, making them ideal for various applications within HRM (Huang et al., 2001; Palos-Sánchez et al., 2022; Qamar et al., 2021). ANNs enhance HRM capabilities by improving the accuracy and objectivity in forecasting recruiting demands and talent selection. By processing large datasets, ANNs can identify optimal candidates' performance and predict future HR needs without human bias (Huang et al., 2001; Qamar et al., 2021).

- Deep Learning (DL), a subset of ML, can significantly enhance HRM through its capability to handle complex datasets and automate decision-making processes (Rodgers et al., 2023).

  DL can handle complex data to perform tasks, significantly enhancing operational efficiency. DL can enhance HRM capabilities across various applications. In image and video recognition, DL algorithms surpass human abilities in analyzing and classifying visual content from thousands of applicants, thereby streamlining candidate evaluation (Rodgers et al., 2023). Similarly, speech recognition technologies powered by DL understand and process diverse human voices and accents, aiding virtual assistants and speech analytics systems in HRM to ensure compliance and manage sensitive data (Rodgers et al., 2023). Additionally, DL supports recommendation engines that personalize employee development programs, aligning learning pathways with individual and organizational goals (Rodgers et al., 2023).

- Natural Language Processing (NLP), combining computational linguistics with ML, transforms HRM by extracting, for example, key information from resumes and automating communication processes, making recruitment more efficient (Rodgers et al., 2023).

  The integration of chatbots trained with NLP capabilities into HR services can understand human language, tone, and context, enabling them to automate and personalize HRM service delivery(Rodgers et al., 2023). NLP has facilitated the move from traditional checklist-based performance appraisals to more dynamic, continuous conversation models. Phone-based apps utilizing NLP software from vendors like WorkCompass analyze a year's worth of employee communications (Tambe et al., 2019). These systems produce comprehensive summaries and comparative analyses, which inform merit pay decisions and other HR processes (Tambe et al., 2019).

  Further leveraging NLP, tools developed by companies such as Vibe analyze the tone of comments posted on internal chat boards (Tambe et al., 2019). This analysis helps predict potential employee turnover, providing early warnings of flight risk. Additionally, NLP tools can detect resistance to change by interpreting the sentiment expressed in employee communications (Tambe et al., 2019).

- Cognitive Computing (CC) brings a human-like understanding and reasoning to HRM, offering comprehensive insights into candidates by analyzing data from various sources, including social media (Finch et al., 2017).

  Using advanced machine learning and linguistics, CC provides HR professionals with insights into potential candidates by synthesizing data from many sources, including social media. Finch et al. (Finch et al., 2017) highlight the efficiency improvements in payroll, benefits administration, and workforce planning attributable to these cognitive technologies. More significantly, the speed and accuracy of recruitment processes are dramatically enhanced; cognitive computing systems can instantaneously deliver a comprehensive 360-degree profile of candidates, ensuring a more targeted and efficient selection process.

- Fuzzy logic, derived from fuzzy set theory, plays a crucial role in HRM by providing a robust conceptual framework for managing uncertainty and vagueness in organizational contexts (Manoharan et al., 2011). Its primary purpose is to enable the operationalization of linguistically expressed knowledge, vital in HRM processes like performance evaluation and decision-making. Unlike traditional binary logic, which limits outcomes to true or false, fuzzy logic introduces a spectrum of truth values between 0 and 1. This multi-valued approach allows HR professionals to use linguistic qualifiers, such as 'often' or 'rarely,' thereby facilitating more nuanced assessments and judgments. For instance, in performance appraisals, instead of classifying employee achievements as simply satisfactory or unsatisfactory, fuzzy logic enables the categorization to reflect a range of performance levels, enhancing the fairness and precision of evaluations.

The practical applications of AI in HRM include anomaly detection, background verification, employee attrition prediction, and content personalization, showcasing AI's vast potential to transform HR practices (Chowdhury et al., 2023; Rodgers et al., 2023). These AI technologies collectively shift HRM from traditional decision-making to strategic planning and ethical consideration, offering transformative potential for HRM and enabling more efficient, accurate, and strategic HR practices.

Appendix C: Promises and Expectations of AI in HRM

This chapter explores the multifaceted role of AI in HRM, distinguishing between the theoretical expectations and the empirical realities. Despite AI's promising applications in HRM, challenges persist in adopting and realizing anticipated benefits. Many companies report limited impact from AI projects, underscoring the difficulties in implementing AI within existing business processes (Chowdhury et al., 2023; Kar et al., 2021; Pan & Froese, 2023; Prikshat et al., 2023). However, the potential for AI to optimize HR functions, particularly in talent acquisition and performance management, remains significant, driven by AI's capabilities in handling large data sets and automating time-consuming tasks (Bujold et al., 2023; Weber, 2023).

Although there is a strong belief in the transformative potential of AI, actual business performance and strategic outcomes often fall short of expectations. The literature indicates that while some organizations anticipate AI to drive innovation and productivity, the practical implementation reveals a more complex scenario fraught with technical and organizational hurdles (Fountaine et al., 2019; Vrontis et al., 2022). While the transformative effects are highlighted in the literature (Budhwar et al., 2022; Palos-Sánchez et al., 2022; Pereira et al., 2023; Rodgers et al., 2023; Vrontis et al., 2022; Zehir et al., 2020), yet the actual impact on businesses, processes, and people remains contested (Chowdhury et al., 2023; Fountaine et al., 2019). Other studies point to a lack of significant progress in AI adoption, emphasizing firms' severe adaptation challenges (Agarwal, 2022; Chowdhury et al., 2023; Coolen et al., 2023). Contrarily, there are reports from early adopters indicating that AI investments have not generated the expected business value (Chowdhury et al., 2023; Fountaine et al., 2019), yet the possibility of AI to enhance business operations continues to be advocated.

Recent findings from a Deloitte survey illustrate the discrepancy between the high deployment of AI technologies and the limited success in achieving tangible business (Mittal et al., 2022). Despite a notable increase in the deployment of AI applications, most firms report only middling results, with continuous investments made in hopes of realizing potential benefits. This suggests a persistent optimism about AI's future role, even in the face of underwhelming performance.

Recent scholarly work highlights the expected benefits of AI in HRM, particularly its ability to enhance decision-making through predictive intelligence. Vrontis et al. (2022) and Chowdhury et al. (2023) emphasize AI's role in facilitating HR analytics, positing that AI can significantly impact HRM processes and practices. Furthermore, Palos-Sánchez et al. (2022) suggest that AI-driven systems minimize errors by processing information more effectively, thereby improving decision-making outcomes.

While the theoretical benefits of AI include enhanced decision-making capabilities, the practical application reveals complexities involving legal risks, ethical considerations, and potential biases... Tambe et al. (2019) discuss the legal constraints faced when AI-driven decisions have adverse impacts, particularly on protected groups. This introduces a considerable challenge, necessitating a deep analysis of the algorithms to ensure they do not unintentionally perpetuate biases. Moreover, algorithmic decisions must be demonstrably justifiable over traditional methods to mitigate legal risks and reduce bias effectively.

The literature often highlights the potential of AI to transform HRM by making processes faster and more efficient. Vardarlier (2020) emphasizes that AI-supported digital systems could streamline recruitment, selection, and orientation, reducing labor and enhancing efficiency. Similarly, Palos-Sánchez et al. (2022) note that 61% of companies utilized AI in 2019 to improve HRM, particularly by automating repetitive tasks, thus allowing HR managers to focus on more strategic activities.

However, the contrasting views on AI's role in HRM regarding personalization and the necessity of human elements highlight a complex balance organizations must navigate. Palos-Sánchez et al. (2022) discuss several issues, including increased job insecurity and anxiety among employees concerned about AI replacing their roles, which could lead to burnout. The dehumanization of relationships, where machines replace human interactions in HRM processes, contributes to a lack of personal connection. Additionally, "techno-stress" from excessive technology use is a growing concern, highlighting the need for continuous training in technological adaptability (Malik et al., 2022; Pereira et al., 2023). Vrontis et al. (2022) remind us that AI should not overshadow the critical human judgment required in HRM. Strategic decision-making, a nuanced understanding of employee needs, and the ethical considerations in managing human resources necessitate a human touch. AI can process data and provide insights, but empathetic, moral, and strategic decisions should ideally remain within the human realm to maintain trust and genuine relationships within the workplace.

While AI presents theoretical benefits, the practical realities often fall short of these theoretical expectations. The widespread adoption of specialized HR tools has inadvertently led to significant challenges in data integration. Organizations frequently employ disparate systems for various HR functions—performance management, applicant tracking, and compensation management—which often results in isolated data silos. These silos not only compartmentalize insights but also hinder holistic data analysis, severely impacting strategic decision-making (Rodgers et al., 2023; Tambe et al., 2019). In many organizations, internal politics further complicate the data integration landscape (Tambe et al., 2019). Moreover, a reliance on basic tools like Excel reflects the rudimentary stage of data management within HR departments, underscoring a pressing need for advanced analytical tools designed for HR purposes (Tambe et al., 2019).

The quality and size of data are critical in leveraging machine learning for HR analytics. For example, Tambe et al. (2019) and Rodgers et al. (2023) highlight that most employers do not collect sufficient data to apply machine learning techniques effectively. The intersection of HR and data science is fraught with challenges due to a fundamental disconnect in expertise. HR departments often lack robust analytical skills, whereas data scientists do not fully grasp HR functionalities (Tambe et al., 2019; Zehir et al., 2020). To mitigate the knowledge gap, there is a need for significant investment in training HR professionals in statistical analysis and scientific methodologies (Palos-Sánchez et al., 2022; Rodgers et al., 2023; Tambe et al., 2019; Zehir et al., 2020). This training would empower HR personnel to interpret and utilize analytics outcomes effectively.

The increased monitoring through AI raises significant concerns about privacy and the ethical boundaries of surveillance (Rodgers et al., 2023). Similarly, incorporating non-traditional data sources like social media has proved valuable for predicting employee behaviors like flight risk. However, Tambe et al. (2019) also highlight substantial ethical concerns regarding the privacy and appropriateness of such data for HRM decisions. Furthermore, AI algorithms can perpetuate and amplify historical biases in the data they process, leading to fairness issues (Tambe et al., 2019).

The complexity of AI algorithms often results in a lack of transparency, making it challenging for employees to understand the basis for decisions affecting them. This obscurity can erode trust in AI-driven HR processes as employees struggle with the implications of decisions they cannot comprehend (Prikshat et al., 2022; Tambe et al., 2019).Additionally, the right to privacy and data protection is complicated by AI, prompting the need for robust legal frameworks such as the GDPR to address these evolving challenges. However, enforcement remains problematic, especially across jurisdictions (Tambe et al., 2019). The EU AI Act, set to take effect in 2024, attempts to address these issues by categorizing AI systems based on risk and imposing strict regulations on high-risk applications. This act mandates transparency, enhances data governance, and ensures compliance with ethical and legal standards, particularly in sensitive areas such as recruitment and performance evaluation (*AI Act*, 2024). While these regulations address critical ethical concerns and foster a trustworthy environment for employers and employees, they also present considerable challenges. Companies, particularly small and medium enterprises (SMEs), may struggle with the resource allocation required for compliance. The need for technical expertise and infrastructure to meet these stringent standards could potentially slow the adoption and innovative use of AI in HR practices across varied business landscapes (Arslan et al., 2021; Bamel et al., 2022; Budhwar et al., 2022).

Appendix D: Breakdown of Performance Management Cycle and Tasks with Examples

Tasks and cycle

This chapter critically examines the convergence of artificial intelligence (AI) with performance management. It specifically explores how AI adoption can be viewed from the well-established performance management cycles proposed by Armstrong and Taylor (2014) and the detailed workflow of performance management tasks outlined by Schleicher et al. (2018). This adoption is analyzed through the lens of current AI applications, providing a practical perspective on how AI can enhance traditional performance management methods.

The performance management cycle, characterized by stages such as performance planning, managing performance, performance reviews, and performance assessment, provides a structured approach to managing and enhancing employee performance. Conversely, Schleicher et al.'s (2018) workflow of performance management tasks—setting performance expectations, observing employee performance, integrating performance information, rendering formal summative performance evaluations, generating and delivering performance feedback, conducting formal performance review meetings, and performance coaching—offers a detailed breakdown of the activities involved in each stage of the cycle. Combining these frameworks aims to leverage the structured performance management cycle while enriching it with specific, actionable tasks that ensure thorough implementation and execution. See Figure 5 for a visualized overview adapted from Armstrong and Taylor (2014) and Schleicher et al. (2018).

This synthesis is particularly relevant in the context of AI's capabilities, which can significantly augment each task within the cycle. AI's role in this enhanced framework is to automate and optimize existing processes and provide advanced analytical tools that lead to more informed decision-making. This chapter will detail how AI can be strategically applied across the combined frameworks to not only streamline processes but also to elevate the performance management process to a level where it can proactively contribute to the organization's strategic goals.

This synthesis is proposed in the context of the theoretical capabilities of AI, which suggest that AI could significantly support each task within the cycle. However, it is essential to acknowledge that while AI offers promising solutions, its practical application in performance management is still evolving. The extent to which AI can truly enhance these processes depends on various factors, including technological advancement, organizational readiness, and the alignment of AI tools with specific performance management goals. Additionally, there is an ambiguity surrounding AI tools. Whether a tool utilizes AI or merely incorporates AI as a buzzword to enhance its market appeal is often unclear. This ambiguity can lead to misaligned expectations. To address this issue, this analysis includes only those tools for which substantial information is available regarding their AI functionalities. This ensures a focused and accurate assessment of how AI can effectively contribute to performance management.

Thus, the objective of this chapter is not to assert that AI will solve all challenges inherent in performance management but to examine the potential ways AI could theoretically augment each task within the combined framework.

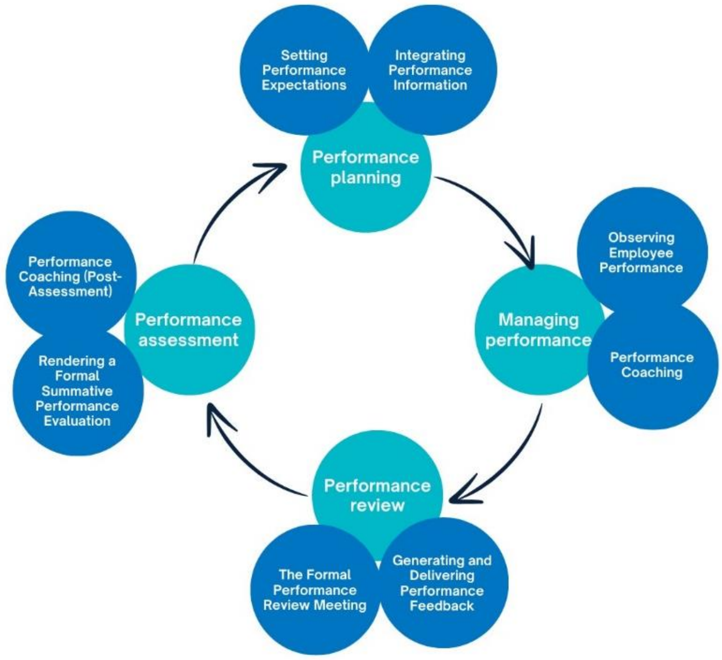

Figure 5. Adapted Performance Management Cycle and Tasks

Performance planning

Performance planning is a crucial component of performance management, focusing on setting clear expectations and aligning individual goals with the organization's strategic objectives (Armstrong & Taylor, 2014). This process involves detailed performance agreements, often rooted in role profiles that outline crucial result areas, the necessary knowledge, skills, abilities, and behavioral competencies required for effective performance. A core aspect of performance planning is establishing objectives or targets, typically guided by the SMART criteria—specific, measurable, agreed, realistic, and time-related—though some adaptations like attainability, relevance, and trackability to enhance the alignment and monitoring of these objectives.

Setting Performance Expectations

AI significantly aids in setting clear, measurable, and attainable performance expectations. Machine learning algorithms analyze historical performance data and industry benchmarks to set realistic employee targets. For instance, AI systems can suggest SMART goals automatically tailored to the individual's role and past performance, ensuring alignment with organizational objectives.

To democratize career development opportunities across all employee levels, IBM introduced an AI-powered personal advisor, Watson Career Coach (Guenole & Feinzig, 2018). The company has implemented an AI-powered personal advisor, Watson Career Coach, to make career coaching accessible to all employees, not just those underperforming or identified as high-potential individuals. The Watson Career Coach functions through a sophisticated system that conversationally engages employees using natural language processing. This AI assistant gathers data about the employee's career aspirations and previous work experiences by asking and answering questions. It integrates this information with historical employment data to form a detailed employee profile.

Furthermore, Watson Career Coach offers a job opportunity matching feature where employees can upload resumes or provide details about their skills. Based on this data, the AI suggests potential job roles within IBM that align with the employee's career goals. Another critical component is the career navigator, which helps employees plan their career paths toward desired roles. It also prepares them for these roles by suggesting specific developmental activities and learning opportunities to acquire the necessary skills.

Integrating Performance Information

AI systems facilitate the integration of diverse performance-related data sources, providing a holistic view of employee performance. These platforms can aggregate and analyze data from various tools like ERP systems, performance tracking software, and employee feedback tools to create a comprehensive performance dashboard accessible to managers and employees.

IBM has further integrated AI into performance management by implementing an analytics-driven solution to infer employee expertise by analyzing enterprise and social data (Varshney et al., 2014). This initiative falls under the broader umbrella of performance planning, explicitly focusing on integrating performance information. The case involves using artificial intelligence to align employee skill data with organizational needs, ensuring performance expectations are based on accurate and up-to-date expertise assessments. The system utilizes a range of data sources, including job titles, human resources information, social tags, and work product data, to predict employees' job roles and specialty areas within the company's structured expertise taxonomy. The AI system at IBM approaches the prediction of job roles and specialties as a supervised classification problem, using a substantial dataset derived from verified employee records as a training set. This application of machine learning is chosen for its generalization accuracy, which has proven effective in handling the classification of complex job role data within the organization. The primary data used includes Job Titles and HR Information; these provide basic but crucial categorical and textual information about employees, and Social Tags and Work Products. These sources offer deeper insights into the practical and social aspects of employees' roles within the company. The integration of this data not only aids in setting accurate performance expectations but also supports various business functions by ensuring that the most current and correct information informs all processes dependent on expert data. For instance, the system's ability to frequently update job roles and specialties significantly enhances strategic planning and talent management.

Managing performance

Managing performance in performance management is a continuous, year-round process integral to standard managerial duties (Armstrong & Taylor, 2014). It revolves around setting clear directions, consistently monitoring and measuring performance, and making necessary adjustments. This ongoing approach is vital for fostering an environment where continuous feedback and development are prioritized over traditional, once-a-year performance appraisals. Such an approach ensures that performance management is an inherent part of daily managerial activities rather than a discrete or isolated event.

The managing performance dimension can be revolutionized by enhancing the interaction between employees and HR services by implementing chatbots. This is exemplified through the initiatives by IBM and PwC, where AI technologies are implemented to streamline processes and enhance the overall employee experience (Guenole & Feinzig, 2018; PricewaterhouseCoopers, 2024).

IBM utilizes AI chatbots across various human resources functions, such as benefits enrollment and compensation planning (Guenole & Feinzig, 2018). These chatbots are tailored to be highly active during peak periods, and some are available 24/7 for continuous employee support, like the new-hire chatbot, which fields approximately 700 queries daily. This system allows for immediate and accurate responses, significantly reducing the workload on HR personnel and enabling them to focus more on complex queries. The result is an enhanced efficiency of HR operations and an improved employee experience through continuous support.

Similarly, PwC has implemented Microsoft Copilot, an advanced AI assistant, to assist employees with administrative tasks like information retrieval from emails, data summarization, and note-taking during meetings (PricewaterhouseCoopers, 2024). This integration with Microsoft 365 tools boosts productivity and creativity. By utilizing data from the user's calendar, emails, and chat history, Copilot efficiently performs its tasks, increasing productivity and reducing repetitive administrative tasks. This allows employees more time for creative and developmental activities, enhancing job satisfaction and workplace dynamics. The AI assistant contributes to performance management by improving the productivity and effectiveness of employees. This, in turn, facilitates a more streamlined approach to managing performance indirectly, as employees and managers can access and utilize information more readily, which supports decision-making processes related to performance evaluations and adjustments.

Observing Employee Performance

Through continuous AI-powered monitoring, managers can observe employee performance in real-time. Technologies like digital dashboards and real-time analytics help track the progress toward goals, identify deviations, and provide timely interventions to steer performance back on track.

In the context of AI in performance management, particularly in observing employee performance, applying intelligent environments incorporating artificial intelligence presents a transformative approach, as described by Aztiria et al. (2013). These smart environments are designed to adaptively learn and respond to the individual behaviors and preferences of employees within the workplace. The system is structured in multiple layers, each contributing to the overall functionality. The first layer processes raw data from environmental sensors, transforming it into insights about user actions, such as when and how employees use certain appliances or facilities. The second layer analyzes this data to identify patterns and regular behaviors, effectively learning from daily activities. The final layer applies these learned patterns to proactively adjust the environment, improving conditions based on individual preferences and habits. Data from motion detectors, temperature sensors, and user interaction with office appliances are crucial for this process, enabling the system to make informed adjustments that reflect usage and preferences.

The study by Carneiro et al. (2017) presents an AI-driven performance management system that leverages non-intrusive monitoring of workers' physical movements and machine interactions to assess mental fatigue. This system utilizes Artificial Neural Networks (ANNs) to process data gathered from accelerometers placed on office chairs and interaction metrics from computer peripherals like keyboards and mice. The ANN uses a multilayer feed-forward architecture trained on a dataset containing behavioral features and subjective fatigue levels users report. This approach allows for continuous, non-intrusive monitoring of performance-related variables, providing organizations with actionable insights into employee wellbeing and performance rhythms, potentially improving management practices and overall workplace productivity. The system's approach is notably non-intrusive, making it an innovative solution in performance management. It assesses mental fatigue without altering employees' routines or invading their privacy, focusing instead on natural interactions with machines and physical posture changes. This non-intrusiveness is a significant aspect, as it enhances worker acceptance and compliance, thereby providing a more realistic and continuous assessment of employee performance without the negative connotations often associated with direct productivity measures. However, while this method avoids direct productivity measurement, its real-world efficacy in improving organizational outcomes and employee satisfaction would require careful implementation and continuous validation to ensure it meets its intended goals.

Performance Coaching

AI-driven coaching tools offer personalized advice based on an employee's performance data. These systems utilize natural language processing (NLP) to deliver coaching tips and motivational feedback specific to the challenges the employee faces, enhancing the coaching process's effectiveness.

At IBM, AI-driven systems are employed to enhance the efficacy of performance coaching by delivering personalized, data-driven insights to managers about their team members (Guenole & Feinzig, 2018). These AI-driven manager talent alerts significantly refine the process of managing and coaching employees by providing actionable insights tailored to the needs of individual team members. IBM utilizes an advanced analytic tool, AI, to analyze many data points concerning employee performance and organizational benchmarks. This system proactively delivers alerts to managers. These notifications provide crucial insights such as an employee's readiness for advancement, potential risk of leaving the company, or likelihood of not meeting performance targets. This allows managers to deliver timely and relevant coaching to each employee based on predictive analytics and real-time data.

The Talent Intelligence Hub, a newly integrated feature of the SAP SuccessFactors Human Experience Management (HXM) Suite, leverages artificial intelligence to enhance performance assessment by advancing a skills-based approach to talent management (Russo, 2023). The Talent Intelligence Hub is designed to shift the traditional emphasis from mere job titles and academic qualifications to a robust understanding of an individual's skills. It facilitates a dynamic skills framework that not only helps assess the current abilities of employees but also aligns these skills with organizational needs to foster growth and adaptability. This system integrates various data sources, including internal employee records and third-party databases, to provide a comprehensive skills inventory that supports informed decision-making in talent management. The hub processes data from multiple sources to develop a detailed skills profile for each employee, encompassing performance evaluations, training histories, and self-reported skills and preferences. Employees are encouraged to manage their growth portfolios, updating their profiles with aspirations and newly acquired skills. This portfolio system recommends personalized upskilling opportunities and aligns potential career advancements with the organization's strategic goals.

Performance review

The performance review phase is a critical element of performance management, serving as a platform to reflect on crucial performance and development issues (Armstrong & Taylor, 2014). It allows managers and employees to engage in a structured dialogue about past performances and future goals. The performance review meeting encapsulates five primary elements: agreement, measurement, feedback, positive reinforcement, and dialogue. This phase culminates the performance management cycle by updating performance agreements based on recent assessments, ensuring that both parties focus on forward-looking strategies to enhance productivity and personal growth.

Generating and Delivering Performance Feedback

Integrating Artificial Intelligence into this process transforms feedback mechanisms, making them more timely, personalized, and actionable. AI technologies have the potential to revolutionize traditional feedback processes by automating data analysis and insights generation, which significantly improves both the efficiency and effectiveness of performance reviews.

The AI-powered 360-degree growth system developed by Zavvy exemplifies the innovative application of AI in performance management (Trisca, 2023). This system automates and personalizes the feedback process, ensuring comprehensive and directly aligned feedback with each employee's developmental needs. Zavvy's AI system automates key components of the feedback process. It can autonomously create and manage feedback cycles, which involves generating reports for recent cycles or initiating new ones. This reduces the administrative load on HR and management, allowing them to focus more on strategic analysis and decision-making than procedural tasks. Additionally, the system can summarize feedback from diverse sources such as self-assessments, peer reviews, and managerial evaluations, providing a consolidated view of an employee's performance that highlights strengths and areas requiring improvement.

The strength of Zavvy's AI system lies in its capacity to personalize the feedback it provides. Based on aggregated feedback and performance data, the AI identifies specific improvement areas for each employee and suggests actionable steps for development. These recommendations are tailored to fit the individual's career trajectory, competency requirements, and insights from previous feedback sessions, making the guidance both pertinent and valuable. Furthermore, the AI uses predictive analytics to forecast future performance trends and pinpoint potential challenges before they manifest. This proactive approach allows managers to offer timely and relevant feedback, helping employees align their performance with the organization's strategic objectives.

The Formal Performance Review Meeting

AI tools can streamline the preparation for performance review meetings by providing automated summaries and talking points based on performance data. These tools ensure that the meetings are focused, productive, and based on objective data, facilitating a more structured dialogue about performance and development needs.

Omni's AI-powered performance review system exemplifies the transformative potential of AI in enhancing formal performance review meetings (Breton, 2023). This system uses AI to streamline the review process, ensure data accuracy, and provide actionable insights for effective decision-making during these meetings. Omni's AI system automates the preparation for performance review meetings by aggregating and analyzing performance data from various sources. This preparation includes generating comprehensive performance reports that summarize employee achievements, highlight areas of concern, and identify growth opportunities. By automating this data compilation, the AI system frees up managers to focus on more strategic aspects of the review, such as coaching and future planning. The AI tool also enhances the effectiveness of the meeting by providing data-driven insights and recommendations. These insights are based on advanced analytics that considers performance metrics and contextual factors such as market conditions, team dynamics, and individual circumstances. This holistic view ensures that the discussions in the review meeting are well-informed and grounded in reality.

Performance assessment

Performance assessment is a critical component of the performance management cycle, typically conducted during or after performance review meetings (Armstrong & Taylor, 2014). It involves comprehensive evaluations based on agreed-upon criteria, aiming to recognize both high achievers and those needing improvement. The goal of performance assessment is to review past achievements and plan future developmental actions. This process benefits significantly from structured frameworks that can provide consistent and objective assessments. Nevertheless, traditional methods often struggle with subjectivity and the inability to differentiate adequately among most employees. This is where AI-driven tools can make a significant impact, enhancing both the accuracy and fairness of performance assessments.

A fuzzy multi-attribute decision-making (FMADM) tool exemplifies an advanced AI implementation in performance management, aiming to create a fair employee evaluation environment (Budhwar et al., 2022; Manoharan et al., 2011). The FMADM model uses AI to process qualitative and quantitative data from employee performance and production databases. Input from evaluators is also incorporated, emphasizing less reliance on subjective judgment and more on systematic analysis. This model translates verbal expressions into numerical data, allowing for quantification of performance criteria that are otherwise difficult to measure accurately. The AI-driven system is supported by tools like Microsoft Excel for calculations, showcasing a blend of simplicity and technological integration. This method ensures that readily available data can be swiftly processed, resulting in actionable insights within minutes. This comprehensive data amalgamation helps identify skill gaps and compare employees to set realistic improvement targets. By fostering a systematic approach to performance evaluation, the organization benefits from a clearer understanding of employee capabilities, streamlined training needs, and more focused human capital development. The strategic use of AI in this model enhances accuracy and provides a dynamic tool for continuous HR improvement.

While the FMADM model introduces precision and reduces biases, its reliance on specific technological tools like Microsoft Excel may limit the scalability and sophistication required for more extensive or diverse organizations. The model also requires consistent updating of the data and criteria to remain effective, which can be resource-intensive. Additionally, the model's effectiveness is contingent on the accuracy and completeness of the input data, posing a risk if data quality is compromised.

Another example proposed in the research by De Oliveira Góes and De Oliveira (2020) combines various computational intelligence techniques such as fuzzy logic, text sentiment analysis, and ensemble classifiers, including multi-layer perceptron neural networks, decision trees, and Naïve Bayes classifiers. By integrating these methods, the system can interpret and analyze performance data with a higher degree of accuracy and fairness. The system functions by aggregating and analyzing performance data collected from employees. This data is processed using the aforementioned computational techniques to yield a more balanced and nuanced interpretation of employee performance. Fuzzy logic allows handling ambiguity in performance criteria, sentiment analysis interprets qualitative feedback, and ensemble classifiers improve prediction accuracy by combining multiple models.

Rendering a Formal Summative Performance Evaluation

AI systems standardize the evaluation process by applying consistent criteria across all evaluations. Advanced algorithms can analyze quantitative and qualitative data to produce fair, transparent, and comprehensive performance assessments free from human bias.

In this practical example, a system is explored that is developed in collaboration with the global human resources (HR) organization of IBM Corporation designed to enhance the formal summative performance evaluation process through advanced AI techniques (Horesh et al., 2016). This system is developed explicitly for IBM Corporation to infer coarse-level, loosely defined expertise areas from big enterprise data characterized by significant volume, velocity, and variety. It is designed to handle large datasets inherent to big enterprises, making it unsuitable for smaller companies with less complex data environments. The system begins by targeting a specific area of expertise and employs an information retrieval component that intelligently indexes and searches through various enterprise data sources. Once relevant data is retrieved, the system applies an information fusion technique to integrate results from multiple queries. This fusion is critical for synthesizing data that vary in value and veracity, ensuring that the most accurate and relevant information is processed.

The core of the system's analytical capability lies in its use of machine learning technologies: low-rank matrix completion and ordinal regression clustering. These methods are instrumental in refining the search results to accurately label employees with their corresponding levels of expertise in specific areas. Matrix completion helps fill in gaps within the data, allowing for a more comprehensive analysis despite incomplete datasets. Ordinal regression clustering, on the other hand, ranks the employees in an ordered manner based on their expertise levels, providing a nuanced understanding of employee skills across the organization.

The Talent Intelligence Hub, a newly integrated feature of the SAP SuccessFactors Human Experience Management (HXM) Suite, leverages artificial intelligence to enhance performance assessment by advancing a skills-based approach to talent management (Russo, 2023). The Talent Intelligence Hub is designed to shift the traditional emphasis from mere job titles and academic qualifications to a robust understanding of an individual's skills. It facilitates a dynamic skills framework that not only helps assess the current abilities of employees but also aligns these skills with organizational needs to foster growth and adaptability. This system integrates various data sources, including internal employee records and third-party databases, to provide a comprehensive skills inventory that supports informed decision-making in talent management. The hub processes data from multiple sources to develop a detailed skills profile for each employee, encompassing performance evaluations, training histories, and self-reported skills and preferences. Employees are encouraged to manage their growth portfolios, updating their profiles with aspirations and newly acquired skills. This portfolio system recommends personalized upskilling opportunities and aligns potential career advancements with the organization's strategic goals.

Performance Coaching (Post-Assessment)

Post-assessment AI tools can help formulate development plans based on the evaluation outcomes. These tools suggest targeted training programs and learning modules to address specific competency gaps identified during the assessment, thereby closing the loop in the performance management cycle.

This is a practical example, particularly emphasizing Performance Coaching and observing employee performance within a large multinational technology company employing over 100,000 individuals across various roles, such as developers, testers, architects, managers, and consultants (Ramamurthy et al., 2015). The company employs an AI-driven analytics framework to manage performance by identifying employees who are potential candidates for re-skilling based on the alignment of their current skills with the organization's future skill requirements. The system leverages data from two primary sources: a skills database that contains self-reported and manager-approved skills with dates of acquisition and a comprehensive human resource database that records historical performance, educational backgrounds, and details regarding employees’ service bands and years in those bands. Using these datasets, the AI models the adjacency between in-supply (current) and in-demand (future) skills and quantifies an employee's likelihood of being successfully re-trained. This modeling approach produces a re-skilling score, which is utilized to recommend candidates for skill development programs. The framework provides strategic benefits by forecasting skill gaps and preparing the workforce for anticipated technological shifts, enhancing the organization's adaptability. Preliminary application of this system has shown that while the initial acceptance rate of recommendations was only 10%, subsequent iterations that incorporated feedback from business leaders and refined the data filters saw an increase in acceptance rates to 46%. This improvement demonstrates the framework's potential to adapt and refine its recommendations based on practical feedback and changing business needs.

Appendix E: Informed Consent Form

You are being invited to participate in the research study titled 'The perception of employees' regarding the adoption of AI in HRM'. This study is being conducted by Mechteld Bakkenes from the TU Delft, as part of a Master's thesis project.

The purpose of this research study is to explore the adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) processes, from the viewpoint of employees. The findings aim to explore the practical applications, challenges and advantages of integrating AI within HRM processes, and to develop strategies that consider employee interests as the key to this technological implementation. The interview will take a maximum of one hour to complete, either online via Teams or face-to-face. Your participation involves answering questions about the use and challenges of AI-HRM in your organization.

As with any online activity, the risk of a breach is always possible. However, to ensure the confidentiality of your responses, the data collected will be securely stored in the TU Delft database. The interviews will be recorded solely for the purpose of this research; recordings will not be published or made publicly available, and they will be deleted after the project is completed, in July 2024. All collected data will be stored securely on the TU Delft drive, accessible only to the research team. Personal data (interview transcript and this signed consent form) will be archived for a period of 2 years after the completion of the study. Data may be reused for future research purposes but only in ways that do not compromise participant confidentiality or the integrity of the original study. The collected data will be used for this Master's thesis, potentially publish an academic paper, and possible future research purposes only, on the topic of AI supported HRM. Quotes from the interview may be anonymously used in publications. The information published in such work will not be traceable to you.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any questions. If you wish your data to be accessed, rectified, or erased, this is possible within one month after the interview is conducted. We ensure that anonymized data will remain confidential and is used exclusively for research and teaching purposes.

If you have any questions about the study or your rights as a participant, please feel free to contact Mechteld Bakkenes (m.g.w.bakkenes@student.tudelft.nl). If you have any concerns or complaints, you can also reach out to Nikos Pachos-Fokialis (N.Pachos-Fokialis@tudelft.nl), who is overseeing this research project. By agreeing to participate, you acknowledge that you have read this opening statement and understand the terms of your participation in this study.

Signatures

______________ ___________________________ _________

Name of participant Signature Date

I, as researcher, have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Mechteld Bakkenes ___________________ _________

Researcher name Signature Date

Study contact details for further information: m.g.w.bakkenes@student.tudelft.nl

Appendix F: Interview Script English

General introduction

Firstly, thank you for your time! During this interview, we will discuss the use of AI in HRM practices of performance management within your organization.

- **Have you received and understood the informed consent form, or do you have any questions about that? If you agree, could you please sign the form?**

Start recording.

As we begin, I'm going to start the recording. Could you please confirm once more that you agree with the informed consent form and the recording?

- To start, could you briefly explain your role and responsibilities within your organization?

AI Use and Performance Management

There are various definitions of AI, and often people mean different things with it. **What do you understand by AI? How would you explain AI?**

For my research, I adopt the following definition**: "artificial tools that can automatically accumulate experience and constantly learn from experience to perform cognitive tasks"**

Performance management: tracking and managing employee performance, i.e. performance evaluation, feedback mechanisms.

Do you use or plan to use AI in HRM processes in your organization?

- **In performance management?**
- *How do you use AI in performance management?*

2. Which tools or software do you use for performance management?
    - Could you describe the specific tools or software your organization uses for integrating AI into performance management?
    - For which aspects of performance management is this tool/software used?
3. **How do you envision the use of AI in performance management?**
    - **For which aspects of performance management?**
4. **What problems could this solve? Why?**
5. What problems did you try to solve with this tool/software?
        - Are those problems solved?
            - If not (completely): Why do you think this is?
            - What did you try to solve those problems? Also other than AI tool/software?

Implementation process

6. Have you been involved in the implemenation process of this tool/software?
    - If yes: Can you remember what motivated you to chose this tool/software, and not a different one? Why?
7. Did you face any challenges with implementing?

- **What challenges do you foresee in implementing AI for performance management?** *Technical / people / organization / external factors*
- Can you describe those challenges?
- How did you try to solve them? **How could that be solved?**
- Are there currently any challenges? *Technical / people / organization / external factors*
    - Do you plan to solve them, and how?

Employee Perceptions

8. **What do employees think of this implementation of AI into performance management practices?**
    - In terms of benefits?
    - And disadvantages? How do you plan to mitigate this?
9. Did employees influence or try to influence the implementation process?
    - If so, how?

Effect of implementation

10. **How has the organization been impacted by this tool/software/AI in HRM?**
    - *Technical / people / organization / external factors*
    - In what ways? Team outcomes?
    - Why do you think that?
11. How have the employees been impacted by this tool/software/AI in HRM?
    - In what ways?
    - Why do you think that?

Strategies for Enhancing AI implementation

12. What actions have you taken, or do you plan to take, to ensure employee interests are considered in the implementation of AI in performance management?
    - From your experience, what approaches would you suggest for effectively incorporating employee interests into AI-driven performance management?

Conclusion

Thank you for sharing your valuable insights!

- Is there anything else you would like to add or any final thoughts you have on the topic?

Thank you again and hope you have a great day!

Appendix G: Detailed Figures from Findings

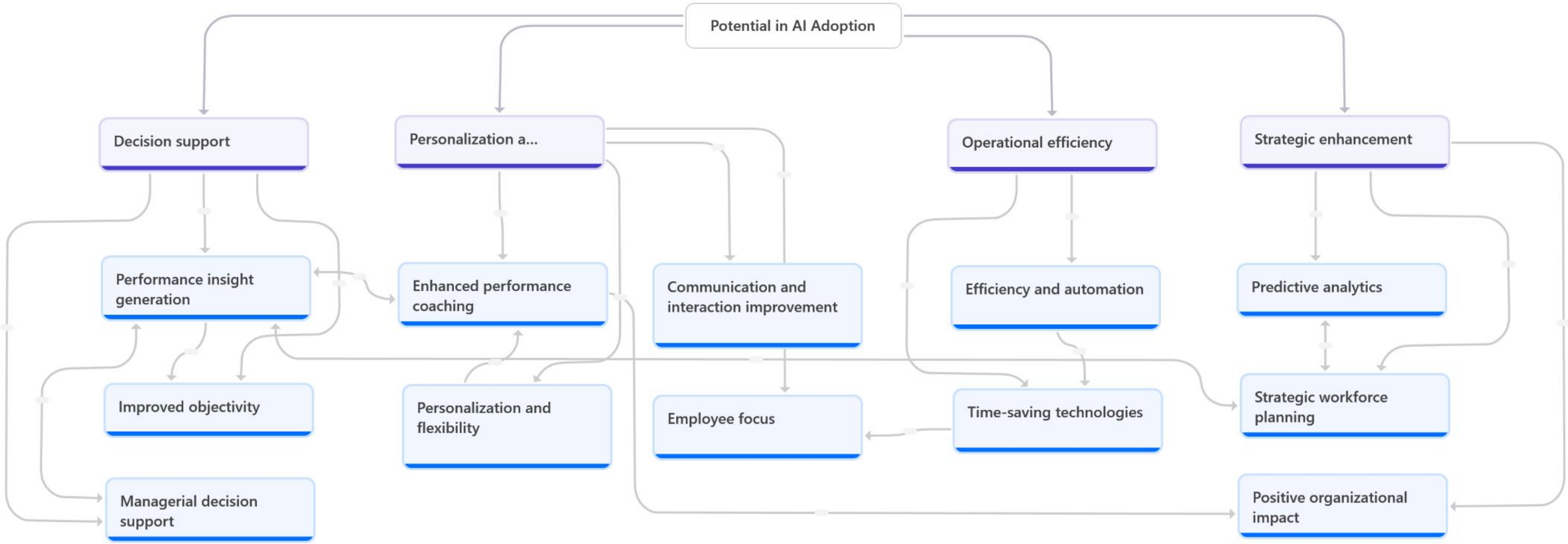

Figure 6. Potential in AI Adoption with associated links

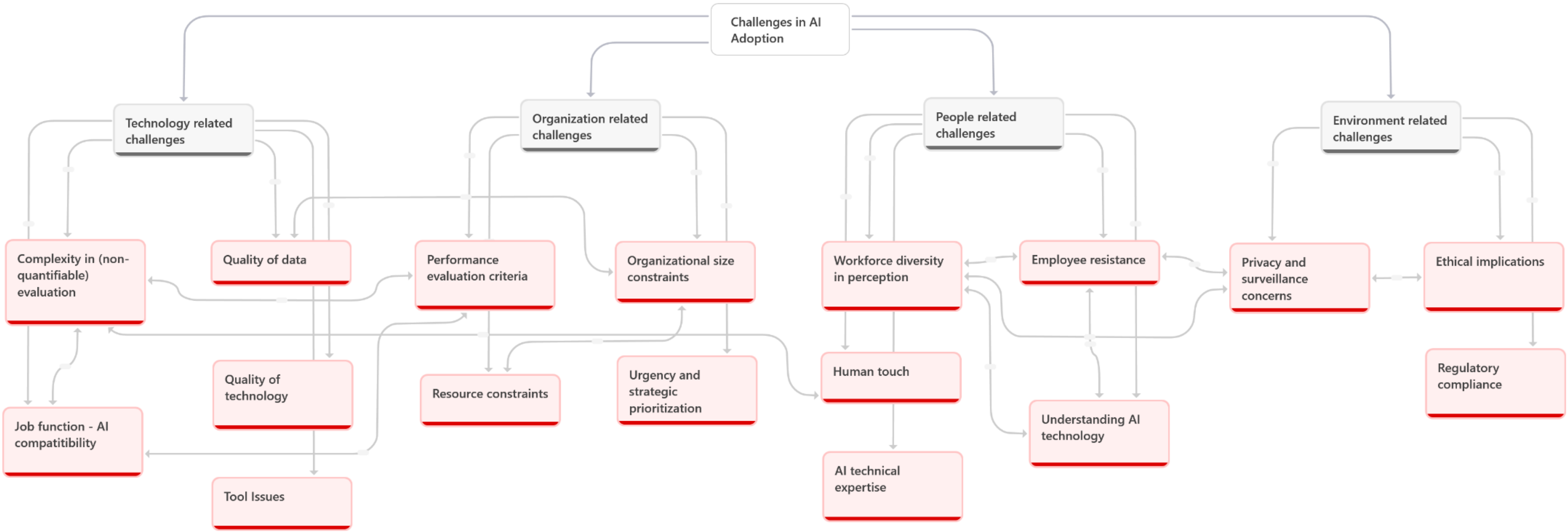

Figure 7. Challenges in AI Adoption with associated links

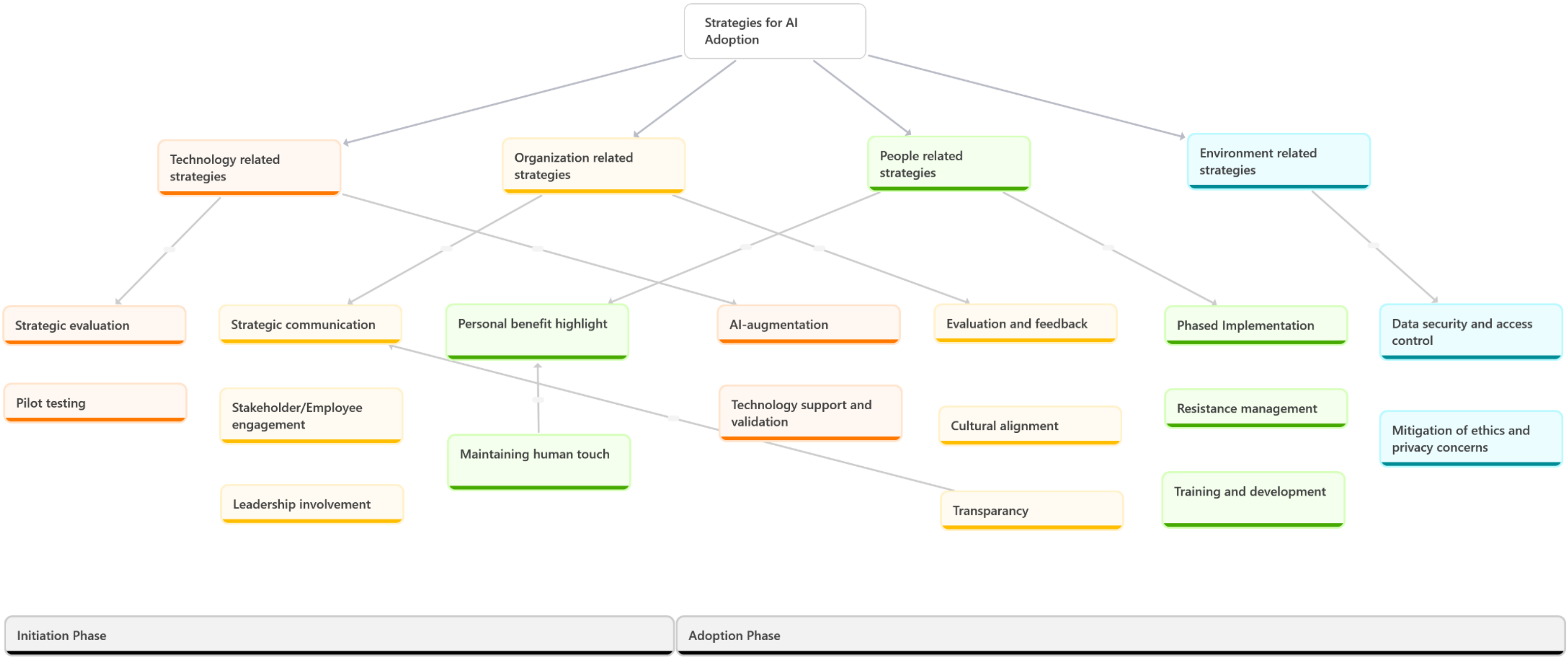

Figure 8. Strategies for AI Adoption with associated links

Figure 9. Co-occurrence of AI Adoption Challenges and Strategies