MASTER THESIS

Is AI a Diamond in the Rough for HR? Identifying the Attributions Towards AI-enabled HR Practices

A Grounded Theory Approach

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PREFACE

This thesis marks the finalization of my Master's in Business Administration with a specialization in Human Resource Management at the University of Twente. For my dissertation, I preferred to escape my comfort zone and decided to academically challenge myself once more. This gave rise to me studying the adoption- and application of the prevalent technological development of Artificial Intelligence (AI) in the Human Resource Management domain. It was my desire to combine this with my passion for understanding the current development and prospective transformation of the Human Resource Management profession.

Exploring the attributions towards AI-enabled HR practices has been challenging. Yet I decided to challenge my limits, and this has provided me with major learning opportunities. I have turned my persistence and curiosity into fascinating insights on AI-enabled HR transformation, and this research has leveraged my enthusiasm for opportunities that I see in the field of HRM and technology. This master thesis named "Is AI a Diamond in the Rough for HR? Identifying the Attributions Towards AI-enabled HR Practices: a Grounded Theory Approach" is a result of commitment, but especially a result of collaboration. For this, I would like to thank some people.

I would like to express my gratitude to my first supervisor, Anna Bos-Nehles for her guidance and support throughout this 5-month process. I deliberately wanted to work with you as a supervisor because of your clarity, structure, constructive feedback, and professional background. I appreciate that at times when I doubted myself, you assured me of my capabilities and supported me by giving suggestions on how to proceed. I will take these final learning opportunities with me into my future career. In addition, I would like to thank my second supervisor, Simon Schafheitle, for the pleasant collaboration, and your open-mindedness that unravelled novel perspectives, not only on this research but during my entire study career at the University of Twente. I also would like to thank all the respondents who participated in this research and who were willing to share their opinions and vision on AI-enabled HR with me. Every conversation has contributed to my learning curve in a unique way. Finally, I would like to express my sincere gratitude towards my parents, Ite and Willy, and towards my brother Mathijs, for their everlasting support throughout my academic career. You have seen me struggling and flourishing and I am very grateful that I was able to share all these moments together with you.

Thank you all for your support which has been instrumental to my student career, but undoubtedly will support me throughout my upcoming professional career.

ABSTRACT

Purpose This research should unravel intentions associated to the adoption- and rejection of AI-enabled HR practices to grasp whether AI could be a diamond in the rough for HR. The purpose is therefore to infer explanations about the willingness concerning the adoption-and rejection of AI-enabled HR practices. The existing knowledge gap is decreased by applying the HR attributional theory in the context of the rapidly revolutionizing AI technology. **Design** This study follows the Grounded Theory Approach in which fourteen semi-structured interviews have been conducted with people in specialist- and managerial functions in HR parts of technology. **Findings** The first section classifies four internal attributions towards the adoption of AI-enabled HR practices. These include autonomous career mapping, self-governed job crafting, sustainable employability, and HR optimization. The desire to adopt AI is in general attributed to the conviction that AI can facilitate the shift from an intuitive reactive HR discipline to a preventive data-driven HR discipline. The external attribution recognized to align with the adoption of AI-enabled HR practices is that of the contagion effect. The second section classifies the attributions of distrust, quality impairment and AI readiness as internal attributions towards the rejection of AI-enabled HR practices. This is followed by the two external attributions of algorithmic exclusion and commercial data exploitation. The transition of AI adoption to AI rejection is fuelled by the transition from AI augmentation to AI automation in decision-making. **Research Limitations/Implications** This study is a cross-sectional study. The attribution theory however stipulates that attributions could change over time. This, together with the rapid revolution of AI, calls for a longitudinal study to identify whether and how the attributions could change over time. Moreover, the attributions concerning AI adoption and AI rejection are in this study based on expectations rather than experiences. Future research should identify experience-based attributions and evaluate whether the intent for adoption also results in actual behaviour that complies with these intents. **Practical Implications** HR software providers, HR professionals and decision-makers involved in the selection process of (AI-enabled) HR software solutions can benefit from the practical insights presented in this study. This study underlines the importance of HR professionals retaining more control than AI in decision-making. This shapes the development of AI-enabled HR software solutions, gives direction to suggestions on AI-initiatives by HR professionals and frames the deployment approach to AI by decision-makers. In addition, the recruitment- and selection practice is identified as the most lucrative and demanding HR practice to integrate supportive AI tools into. This provides all parties with a starting point to reinvent HR by means of AI. Concerns on complexity and data exploitation gives rise to a critical reflection on how parties are constituting transparency and internal- and external data security. **Originality Value** The novel perspective this study adopts is related to defining an HR attributional theory in the context of AI, which not only covers the existence of AI-enabled HR practices in organizations, but also anticipates the polarizing context by reviewing the absence of AI-enabled HR practices in organizations. **Keywords** Artificial Intelligence, Human Resource Management, Attributions, HR attributional theory, AI augmentation, AI automation, Paradox, Industry 4.0

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1. | INTRODUCTION

This chapter familiarizes the reader with the situation and complication, introduces the research objective and research questions, explains the theoretical- and practical contributions, and presents the outline of this study.

1.1 | Situation and Complication

Artificial Intelligence (AI) is the rapidly revolutionizing industry 4.0 technology that is nowadays referred to as Wall Street's latest craze (La Monica, 2023, title). Within a century from AI's birth in the 1940s (Haenlein & Kaplan, 2019), we have arrived at AI's season of fall. A season in which we harvest AI's application to a huge variety of domains that were once unthinkable. But what does this quickly emerging AI technology exactly entail? AI technology enables machines to perform and fulfil tasks that would normally require human intelligence (Bhardwaj et al., 2020; Russel & Norvig, 2016; Tambe et al., 2019). An AI system is able to think and learn and employs its learning function to achieve specific goals in a flexible manner, mimicking human cognition (Kaplan & Haenlein, 2019). The unprecedented growth of the application of AI technology in the corporate world has generated sweeping transformations across different industries and domains (De Lima, 2022). The year 2023 has been exemplary for how AI started transforming the face of Human Resource Management like never before. Imagine recruiters advising candidates to use ChatGPT when applying for jobs (Lindzon, 2023) and lawmakers in the United States working on the federal- and state level on legislation towards AI-enabled recruitment (Christian, 2023). With the rapid development of AI technology running parallel to the seismic and unpredictable shifts in the world of work (Reimert, 2023) it is imperative to understand why companies choose to capitalize the power of AI for HR purposes or why they remain disengaged in basing HR practices on AI.

The HR domain is battered by instability (Gurchiek, 2022) as it is finding itself in politically unstable times, an unstable economy, and more importantly unstable periods of employment relations (Crowther, 2022). Unlocking the value of AI could satisfy the HR discipline by harnessing benefits such as job upgrading, task automation, increasing efficiency, cost reductions, improving decision-making, and enabling time for human value creation (Bhardwaj et al., 2020; Buck & Morrow, 2018; Du & Xie, 2021; Pan & Froese, 2022; Sander & Stroet, 2020). However, the technological advancements and pace of development simultaneously highlight the reverse of the medal that could cause reluctance towards the integration of AI in HR. There is great apprehension for the prospective HR discipline in which the power of AI is capitalized, as this technology is also associated with job replacement, social inequality, and making humans obsolete and passive. Additionally, AI brings into existence concerns about privacy, digital safety, and reputation (Cheatham et al., 2019; Du & Xie, 2021; Dwivedi et al., 2021; Pan & Froese, 2022; Sun & Medaglia, 2019).

Will AI disrupt or reinvent HR? It seems that there are two narratives in which the 'main character' ought to be uncertainty. Nowadays, organizations are expected to keep up with technological advancements while it is actually uncertain what it will exactly bring the organization.

This uncertainty gives rise to the widely diverged perspectives, captured by organizations, managers, and employees, towards AI-enabled HR practices. Here we face the crux of the matter: the paradox this industry 4.0 technology entails. The extensive paradoxical perspectives that are common through literary works (Du & Xie, 2021; Pan & Froese, 2022) have become inherent to AI's general prevalence. Therefore, attention must be paid to how these generic paradoxical views are translated into convictions thriving AI adoption, or concerns obstructing AI adoption in the HR discipline.

Therefore, to understand whether and why AI could be a diamond in the rough for HR, common sense explanations about both, the adoption- and rejection of AI-enabled HR practices must be unravelled. Nishii et al. (2008) already identified such common sense explanations about the existence of generic HR practices. The existence of generic HR practices was investigated based on the HR attributional theory which theorizes that employees respond differently to HR practices based on the attributions they make towards managements' intentions of implementing these (Nishii et al., 2008). Their research therefore examines the relationship between the attributions employees make towards the existence of a HR practice and how that affects their attitude and behaviour in terms of satisfaction and commitment (Nishii et al., 2008). With AI technology being heralded as a tool to better anticipate the seismic shifts in the world of work, it came as a surprise that the HR attributional theory has not been applied yet in the context of AI. Whereas research has emphasized the importance to recognize and comprehend the attributions made towards generic HR practices, it has thus far neglected to integrate the AI context into the HR attributional theory. Great relevance is attached to identifying attributions towards AI-enabled HR practices as this present era is characterized by the booming AI technology running parallel to an increasingly unstable HR landscape. Exploring these attributions allows one to comprehend why this Wall Street craze is either deemed to contribute to HR's reinvention or why it is rather associated with the disruption of HR practices. Moreover, it allows one to understand the balancing act between the paradoxical perspectives on AI's application in the HR domain.

1.2 | Research Objective and Research Questions

This study aims to infer explanations that unravel the emotions, convictions, and thoughts that are attributed to the adoption- and rejection of AI-enabled HR practices. To derive these explanations, we must retrieve the vision of how AI-enablement is expected to improve or impair HR practices such as recruitment and selection, onboarding, training and development, performance management, retention, advancement, employee compensation and benefits, leave and attendance, and strategic HR planning (Bhardwaj et al., 2020; De Leede, 2022; Tambe et al., 2019). This research is therefore characterized by the objective to identify the attributions towards AI-enabled HR practices. To achieve this goal, the following exploratory research question should be answered:

"What are the attributions towards AI-enabled HR practices?"

To be able to derive structurally at an answer, two sub-questions have been defined. These are:

1. *"What are the attributions concerning the adoption of AI-enabled HR practices?"*
2. *"What are the attributions concerning the rejection of AI-enabled HR practices?"*

1.3 | Theoretical Contributions

By answering the research question, this paper constitutes three theoretical contributions. First, this research extends the current HR attributional theory developed by Nishii et al. (2008) as it identifies attributions towards AI-enabled HR practices. This is essential as people may attribute different emotions to AI-enabled HR practices than they do to generic HR practices. As HR practices ought to be supported or even replaced by AI in the future, it is of crucial importance to infer attributions in this context of AI advancement. To constitute this, this research takes on the perspective of people in specialist- and managerial functions in HR parts of technology. Second, this research diverges from papers written by Hewett et al. (2018), Nishii et al. (2008), Özçelik and Uyargil (2020), and Wang et al. (2021), as this study does not address the effects of these attributions in relation to specific employee behaviour and attitudes. By identifying the attributions towards AI-enabled HR practices that capture multi-dimensional perceptions and purposes explaining the intent of the decision, this paper rather addresses the drivers of AI rejection or AI adoption concerning HR practices, building further on the research of Tambe et al. (2019). Third, the 'why' perspective approach of this study constitutes scientific understanding on the intent stimulating AI adoption or AI rejection concerning distinctive HR practices. This study contributes to theory as it subsequently develops two typologies towards the adoption- and rejection of AI-enabled HR practices that could serve as a theoretical framework for future studies examining the alliance or alienation between AI and HRM. It therefore constitutes a step forward, synergizing the strategic HR- and HR technology literature and contributing to this by establishing a context-specific paradigm on the HR attributions in the polarizing context of AI adoption and AI rejection.

1.4 | Practical Contributions

Answering the research question also gives rise to several practical contributions. The practical contributions to HR software providers are fourfold. First, this research is of great relevance to companies developing and providing HR software solutions as it examines how the booming AI technology is preferred to be deployed to anticipate the seismic and unpredictable shifts in the HR discipline. Thereby it narrows the extensive AI features to a few specific AI features that are considered a must-have regarding its integration in AI-enabled HR software solutions. Second, this relevance becomes reinforced once these specified AI features are aligned to designated HR practices considered most promising for AI adoption. The synergy between HR's ruling demands and AI's trademarks leverages a guiding principle that is convenient for organizations in granting investment opportunities in their research- and development phases of AI-enabled HR software solutions.

Third, by knowing the attributions towards the adoption of AI-enabled HR practices, HR software providers know how people in specialist- and managerial functions in HR parts of technology perceive the benefits of AI. This serves as valuable input for their future marketing- and communication claims. Fourth, as this research also recognizes the attributions towards the rejection of AI-enabled HR practices, it shows practical relevance as it not only signals the critical risks but more importantly explain when and how these risks become decisive towards the rejection of AI in HR. This shapes the direction for developing AI-enabled HR software solutions that are likely to gain acceptance.

Finally, this research serves practical relevance towards HR professionals and organizational decision-makers involved in choosing new HR software solutions. The practical relevance to HR professionals can especially be traced back to the novelty of AI adoption in performing HR practices. Whereas HR professionals might know they need to change HR practices to become resilient against the prevailing instability, they might not know how to facilitate this. This research provides insights on the attributions towards adoption that explain why organizations capitalize the power of AI for the performance of HR practices. This could create awareness of how change can be enabled by AI. As this research also stipulates concerns that are decisive towards the rejection of AI-enabled HR practices, it also alarms HR professionals about the negative effects that AI-enabled HR practices could constitute. This research could therefore subsequently aid thoughtful strategic decision-making towards decision-making units that face the process of choosing new (AI-enabled) HR software solutions.

1.5 | Outline of the Study

This study starts with examining the background of existing literature on AI and its integration in the HR domain. Subsequently, it outlines the existing HR attributional theory and relates this to the AI context. This is followed by the methodology section, which presents the research strategy conducted to perform this research. Afterwards, the results are presented. The final sections cover the discussion and conclusion in which the main findings concerning the attributions towards AI-enabled HR practices are presented and elaborated upon.

2. | THEORETICAL BACKGROUND

This chapter familiarizes the reader with the theoretical concepts of AI, Machine Learning, and Deep Learning. It portrays the considerations and concerns associated with the integration of AI into the field of HRM. Finally, it apprises the reader about the HR attributional theory and its association with AI.

2.1 | An Introduction to the Industry 4.0 Technology AI

AI technology gains ground in more and more domains which is likewise reflected by its abundant display in academic articles and (social) media platforms. Yet, it remains surprisingly difficult to decide on AI's definition (Kaplan & Haenlein, 2019). This is partly related to the pace of developments. Humans' interpretation and classification of intelligence evolves over the years by keeping track of technological advancements (Kaplan & Haenlein, 2019). To define AI for the purpose of this research, the term Artificial Intelligence is first decomposed. 'Artificial' means that something is made by human beings and the forthcoming 'artificial' product or service reflects a copy of something natural (Cambridge Dictionary, 2023a; Merriam Webster, 2023). 'Intelligence' is referred to as one's ability to learn, comprehend, and develop judgements and opinions that are reason-based (Cambridge Dictionary, 2023b). Originating from the previous definitions, AI in this research would identify with machines that have copied human intelligence to enable that system to learn from data, comprehend and identify data patterns, and develop judgements based on these patterns. As a formal definition, AI in this research is therefore referred to as the ability of systems to interpret external data correctly and to learn from this which allows the AI system to perform and fulfil tasks, that would normally require human intelligence, through flexible adaptation (Bhardwaj et al., 2020; Kaplan & Haenlein, 2019; Russel & Norvig, 2016; Tambe et al., 2019).

To delve into the adoption- and application of AI in the HRM profession, one must be aware of the three AI classifications that allow AI to serve distinctive purposes. Firstly, mechanical AI is allocated as the most rudimentary AI classification. Mechanical AI is designed to automate repetitive tasks (Huang & Rust, 2021), with the primary objective of maximizing efficiency and minimizing variability (Huang & Rust, 2021). Secondly, thinking AI is employed for data processing and decision-making (Huang & Rust, 2021). Thinking AI should enable service personalization by offering data-based predictions and suggestions (Huang & Rust, 2021). Critical in this are the volume (amounts of data), velocity (frequency of updated data), and variety (data categories) (Kaplan & Haenlein, 2019). Thirdly, the most advanced AI design is feeling AI, which allows for analysing and comprehending human emotions (Huang & Rust, 2021). This AI discipline is critical in maintaining relationships (Huang & Rust, 2021). AI is generally introduced to automate processes, increase effectiveness and efficiency, and eliminate repetitive tasks such that humans can focus on human-enhanced value creation. It moreover simplifies and speeds up practices, allows for evaluation and prediction, and supports and fosters decision-making (Bhardwaj et al., 2020; Buck & Morrow, 2018; Sander & Stroet, 2020). AI is often simultaneously mentioned with the terms Machine Learning and Deep Learning, these techniques are considered to be the fuel of AI and are therefore clarified in the upcoming paragraph.

2.2 | The Fuel of AI: An Introduction to Machine Learning and Deep Learning

A discipline of AI that has emerged and gained popularity in the past two decades is Machine Learning (ML) (Jordan & Mitchell, 2015). ML is a subset of AI in which computing systems employ large amounts of data to learn how they should perform tasks (Oxford Learner's Dictionaries, 2022a). Computing systems employ algorithms and statistical models which allow them to execute tasks for which they are not explicitly programmed (Mahesh, 2020). Rather than programming the system, it ought to be easier and more effective to train a system by showing examples of "desired input-output behaviour" (Jordan & Mitchell, 2015, p. 255). ML enables computing systems to advance their intelligence every time they obtain new data (Oxford Learner's Dictionaries, 2022a; Mitchell 2006). Where humans learn from past experiences, computing systems learn from past data. The performance of algorithms therefore improves as they are exposed to more data over time (Alzubaidi et al., 2021). The advantage of ML is scope oriented, as ML can outperform humans in recognizing patterns within large amounts of data (volume, velocity, and variety) (Kaplan & Haenlein, 2019).

Finally, a subset of ML is known to be Deep Learning (DL) (Gupta et al., 2021). DL is a ML technique that educates computing systems to do things that come naturally to humans (MathWorks, n.d.). DL employs several processing layers to unravel patterns and structures in extensive data sets (Rusk, 2016). DL imitates the human brain. Whenever a human brain retrieves new information, it enters the process of sense-making by comparing this new information to the information that is already known. Through the process of labelling the brain deciphers the information and assigns components to distinctive categories. DL deploys a similar approach; it emulates biological neural networks. This imitation is referred to as Artificial Neural Networks (ANN) (Jakhar & Kaur, 2020). Table 1 presents an overview of the definitions of AI, ML, and DL, serving as the foundation that is necessary to grasp the upcoming review of AI-enabled HR practices.

Table 1: Definition overview of AI, ML, and DL

Term	**Definition**
Artificial Intelligence (AI)	The ability of systems to interpret external data correctly and to learn from this which allows the AI system to perform and fulfil tasks, that would normally require human intelligence, through flexible adaptation (Bhardwaj et al., 2020; Kaplan & Haenlein, 2019; Russel & Norvig, 2016; Tambe et al., 2019).
Machine Learning (ML)	Rather than by explicit programming, machines advance their intelligence on how to perform tasks by learning from desired input-output behaviour (Jordan & Mitchell, 2015; Mahesh, 2020; Mitchell, 2006; Oxford Learner's Dictionaries, 2022a).
Deep Learning (DL)	Machine learning algorithms that imitate the thinking process of the human brain which allows them to learn from data (Gupta et al., 2021; Jakhar & Kaur, 2020).

2.3 | Shining a Light on AI-enabled HR Practices

HRM encompasses distinctive HR practices that could be enabled by AI, these practices are specified as follows: recruitment and selection, onboarding, training and development, performance management, retention, advancement, employee compensation and benefits, leave and attendance, and strategic HR planning (Bhardwaj et al., 2020; De Leede, 2022; Tambe et al., 2019). AI enablement can be initiated by both augmentation and automation. AI augmentation refers to the collaboration between humans and AI in performing tasks, whereas AI automation implies that AI takes over a human task (Raisch & Krakowski, 2021).

Academic research implies that AI could exhibit a shift in the approach to HR activities such as recruitment and selection. Seen from a conventional perspective, managers and HR professionals tend to make decisions on gut feeling (Ahmed, 2018). Yet, AI-enabled recruitment and advancement could qualify these HR practices as data-driven. AI could constitute benchmark criteria, based on high-performer profiles, which initiates the process of finding suitable internal candidates (selection) or external applicants (recruitment). Evaluating assessments against these criteria makes AI exhibit its predictive power to determine who is likely to perform best in a new specific function (Cheng & Hackett, 2021). It even grants the opportunity to analyse and decode video interviews, by interpreting signals that could determine a candidate's probability of success (Ahmed, 2018). Similarly, organizations could deploy AI, in terms of an augmentation approach, to foster talent acquisition and internal mobility. HR practitioners could collaborate with AI solutions to identify predictive parameters for a candidate's future job performance (Raisch & Krakowski, 2021). The initial augmentation approach could in due course result in automated candidate assessment procedures, eliminating human intervention (Raisch & Krakowski, 2021). Strategically seen, AI is moreover perceived as a critical technology that possesses the predictive ability to identify competence gaps, which recruitment and selection-, advancement-, and training and development activities could anticipate (Cheng & Hackett, 2021; De Leede, 2022).

Tambe et al. (2019) also recognize the potential of AI in the HR practice of onboarding. Transforming the onboarding process into an AI-enabled activity would offer managers the opportunity to fathom which onboarding practices allow for quicker completion of the onboarding period (Tambe et al., 2019). On top of that it could direct new employees in their onboarding period through personalized employee experiences. AI could facilitate personalized messages and notes that inform the employees of the names, locations, and contact information of people they could connect with within their first weeks. This satisfies personal desires (social exchange) as well as professional purposes (information exchange) (Ahmed, 2018).

The shift from intuitive decision-making to data-driven decision-making is according to Kaplan & Haenlein (2019) also critical regarding the HR practice of training and development. Based on intuition, employees could identify learning opportunities, but that does not mean it matches the preferred business goal: increased performance, measured by specific parameters for that particular job.

Algorithms allow for a data-driven decision-making process in the allocation of training- and development opportunities by monitoring skills, behaviours, and activities of for instance the organization's high-performers. Again, this could serve as benchmarking criteria (Kaplan & Haenlein, 2019). Comparing these criteria to personal data allows the software to determine interventions that improve one's performance (Tambe et al., 2019). The pace of AI developments and the increasing lifespan of employees in terms of age shed a whole new light on the concepts of career flexibility and lifelong learning (Kaplan & Haenlein, 2019).

In the field of performance management, AI ought to contribute to the process of evaluation and revision. The generated data shapes the foundation to evaluate whether implemented practices and training opportunities enhanced job performance (Tambe et al., 2019). Based on AI algorithms, suggestions could emerge that direct organizations in the revision process of training choices. Furthermore, AI-enabled performance management could transform this HR practice into a proactive activity in which employees are provided with real-time feedback through for instance a chatbot (Buck & Morrow, 2018).

Finally, AI helps to forecast which employees would like to leave their jobs voluntarily, also known as employee turnover (Ahmed 2018; Schafheitle, 2022; Tambe et al., 2019). Data is generated by tracking computer activities, use of language in e-mails, and internet browsing. By deploying AI analytics, potential turnover risks could be identified about which the employer could be alerted. The retrieved insights could furthermore serve to develop and shape retention strategies. Patterns could emerge from data that could be traced back to specific circumstances that have caused changes in employee behaviour. These circumstances are a red flag to organizations as they might be related to the employee's intention or thoughts of leaving (Ahmed, 2018).

Whereas the previous examples have indicated that AI technology could be embraced throughout the entire employee life cycle, one cannot deny the concerns that are associated with its application in the HR domain.

2.4 | Considerations and Concerns Related to AI integration in the HRM Domain

Despite the previously mentioned promising AI features the HR profession could benefit from in all layers of their HR activities, a cautious approach to the deployment of this rapidly revolutionizing technology is still common (Duan et al., 2019; Dwivedi et al., 2021). On the one hand, the pace of AI's development is something that is currently admired. Admiration is reflected in the extent of how helpful this industry 4.0 technology currently already is. The improved decision-making, enhancement of efficiency, and self-improving learning ability that constitutes fast developments reflect the advantageous contribution of AI towards organizations (Du & Xie, 2021).

On the other hand, these fast developments and changes introduce the downside of AI, the concerns of people captured in social-, economical-, and ethical challenges (Du & Xie, 2021; Duan et al., 2019; Dwivedi et al., 2021). Research implies that organizations' inclination towards AI adoption reflects firstly a social concern that is related to the expectations and values associated with AI. The lack of knowledge of AI results in unrealistic assumptions and obstructs the (extended) adoption of AI technologies (Dwivedi et al., 2021; Sun & Medaglia, 2019). Secondly, once organizations know how AI could be of added value to their organization and once they consider adopting AI-enabled software, economic challenges might occur in terms of required financial investments (Dwivedi et al., 2021). Yet, from the perspective of the employee as well as from a managerial point of view, the biggest concern appears to be ethical.

It appears that almost "half of all employees are wary about trusting AI at work" (Curtis, 2023, section 3). Whereas some believe that AI ought to make humans passive, dependent, and obsolete (Du & Xie, 2021), the lack of trust is profoundly thrived by the prominent ethical concern that AI jeopardizes the privacy and digital safety of employees. Privacy ought to be infringed upon if organizations are not transparent about their AI use. Once employees discover the opaque approach towards the application of AI technology, they become concerned about their autonomy and whether the AI adoption complies with their privacy rights (Cheatham et al., 2019; Tursunbayeva et al., 2021; Tong et al., 2020). The opacity moreover obstructs employee performance as their trust is damaged and they no longer understand the organizational landscape they act in (Gal et al., 2020; Tursunbayeva et al., 2021). In addition to jeopardizing employees' trust, this confronts employees with fears such as loss of control and disruption of relationships and plans (Roe, 2018; Tong et al., 2020). Another prevailing ethical concern is the fairness of AI systems. Arguments that would favour an organization to deploy AI is to eliminate bias in human reasoning (Tursunbayeva et al., 2021). The intention to establish for instance a fairer hiring practice goes nevertheless hand in hand with the worry that discrimination is reintroduced by algorithms as they ought to take over the prejudices of humans. These concerns especially prevail when AI systems retain more control than humans. This negatively impacts the trustworthiness of the hiring practice (Curtis, 2023; Tursunbayeva et al., 2021). AI automation is also exposed to ethical concerns in performance management (Curtis, 2023). Reducing people and performance to numbers namely devalues characteristics that cannot be measured by solely AI and data (Tursunbayeva et al., 2021).

It could be said that the seismic shift from human-enabled HR activities to AI augmented or AI automated HR activities raises quite some concerns that could damage employees' trust in AI (Cheatham et al., 2019; Curtis, 2023; Tong et al., 2020; Tursunbayeva et al., 2021). Yet, what about the additional perceptions of organizations? The novelty of AI combined with its rapid advancement might confront organizations with the inability to identify potential failure indicators (Calvard & Jeske, 2018; Tursunbayeva et al., 2021). Organizations are concerned that due to the lack of knowledge of the 'unknown', the rules are not imposed to the extent they should be. Managing the unknown is considered to be a significant challenge, as the riskiest consequences are ought to be those we are currently not aware of (Cheatham et al., 2019).

Organizations are specifically concerned about moral issues like data-sharing and data-usage for unknown purposes, which could affect the organizations' reputation (Cheatham et al., 2019; Dwivedi et al., 2021; Sun & Medaglia, 2019). Pertaining this to the HR discipline it makes one wonder whether AI is able to grasp the complexity of HR outcomes (i.e., when is someone a good employee?). Moreover, the ethical concern on fairness turns into legal concerns once organizations deploy prediction algorithms to hire and fire employees. Legal frameworks require organizations to explain and justify why the decision being made is fair. This is considered very challenging with the deployment of AI technology (Tambe et al., 2019).

To be able to comprehend how the mechanism of AI adoption in HR relates to these ethical concerns, one must first gain an understanding of the concept of attributions and the HR attributional theory that serves as the foundation of this research.

2.5 | The HR Attributional Theory Defined

The attribution theory expresses that people possess causal explanations about why things happen, and translates these perceptions into attributions (Hewett et al., 2018; Nishii et al., 2008). Formally, an attribution is defined as "the act of saying or believing that something is the result of a particular thing" (Oxford Learner's Dictionaries, 2022b, section one). People have causal explanations about the existence of situations and behaviour, and these perceptions are captured as attributions (Hewett et al., 2018; Nishii et al., 2008). The Austrian Psychologist Fritz Heider emphasized this human need for common sense explanations, which are required to control, predict, and make sense of situations (Hewett et al., 2018). The HR attributional theory indicates that employees have causal explanations about why HR practices exist, and these perceptions are captured as attributions. The attributional theory in the HRM domain has thus far focused on the perceptions employees have about the existence of general HR practices.

Nishii et al. (2008) developed a typology of HR attributions that identifies five causes employees could infer for why HR practices exist: (1) to improve quality/performance; (2) to foster employee wellbeing; (3) to exploit employees; (4) to diminish costs; (5) to act in accordance with union demands. Research has found that the internal commitment-focused HR attributions, service quality and employee well-being, are positively related to employee attitude, which is conceptualized as affective commitment and satisfaction (Nishii et al., 2008). On the opposite, the control-focused internal attributions, cost reduction and employee exploitation, are negatively related to employee attitudes. Research has also elaborated that the external attribution of union compliance is not related to employee attitudes, because employees perceive such events to be out of organizations' control (Hewett et al., 2018; Nishii et al., 2008). Concerning the attributions, internal attributions are those the organization can exert control on, while on the opposite, external attributions are ought to be out of the organizations control (Nishii et al., 2008).

2.6 | The HR Attributional Theory in an AI Context

As expressed, AI could enable a transformation, development, and advancement of HR practices but its introduction and adoption also come with concerns and challenges. To understand why organizational decision-makers either adopt or reject AI-enabled HR practices, one must understand the trade-off between the aims that favour the AI application in HR and the considerations that obstruct its integration. This desire to make sense of situations is a human trait (Hewett et al., 2018) that especially prevails when there are polarizing storylines about one and the same concept: in this case AI integration in HR (Willcocks, 2020). The perceptions on whether people expect to flourish or wither by either engaging in- or remaining alienated from the booming AI technology reflects a viewpoint. These viewpoints become valuable once we can adhere common sense explanations to these. This signifies the importance of comprehending the balancing act between organizational HR demands, AI features, and the thoughts, convictions, and emotions attributed to the alignment of these. The HR attributional theory serves as the foundation of this study as this research requires a domain-specific approach on the 'why' perspective (Nishii et al., 2008). This theory allows for recognizing the attributions made towards the sincere purposes explaining the adoption- or rejection of AI-enabled HR practices, while simultaneously accounting for the current specific timeframe that allows these attributions to develop.

While knowing that AI is generally introduced to automate processes, increase effectiveness and efficiency, and eliminate repetitive tasks such that humans can focus on human-enhanced value creation (Bhardwaj et al., 2020; Buck & Morrow, 2018; Sander & Stroet, 2020), this may not reflect the reasons why one wants AI to exist in the specific HR discipline. The HR attributional theory by Nishii et al. (2008) makes us in current times wonder which intentions prevail when preferring to leverage AI in the HR discipline. Is the adoption thrived by the hype of AI reflected by the increasing pervasiveness of AI in managerial contexts (Kaplan and Haenlein, 2019), or is it directed by AI's qualities envisioned to contribute to achieving objectives? And do these attributions subsequently reflect organizational interests, employee interests, or both? These questions are accounted for by the first pillar of this research: the identification of the attributions concerning the adoption of AI-enabled HR practices (sub-question one).

While knowing that the deployment of AI technology gives rise to ethical enquiries in terms of privacy infringement that ought to reinforce discrimination and loss of autonomy (Du & Xie, 2021; Dwivedi et al., 2021; Tong et al., 2020; Tursunbayeva et al., 2021), this might not explain decisive constraints towards AI adoption in the HR discipline. By consulting the 'why' perspective the concerns thriving the reluctance towards AI-enabled HR practices should be identified. Comparing this to the generic HR attributional theory, makes us wonder whether the purposes for rejection differentiate between organizational- and employee interests. Moreover, is reluctance mostly associated with matters organizations can exert control on or not? These questions are accounted for by the second pillar of this research: the identification of the attributions concerning the rejection of AI-enabled HR practices (sub-question two).

To reflect the contrasting storylines, and to unravel the decision breakers- and makers in terms of AI adoption in HR, two typologies must be developed. It is imperative to grasp an understanding of common sense explanations towards the adoption- and rejection of AI-enabled HR practices to be able to determine whether AI can be a diamond in the rough for HR. While being aware of how the HR practices, composing one's entire employee life cycle, can be transformed by AI (Tambe et al., 2019), the two typologies of attributions ultimately reflect the potential reinvention of HR activities. This is the case as the effect constituted by AI resides in the attributions made towards them (Nishii et al., 2008).

3. | METHODOLOGY

The primary purpose of this study is to develop an understanding of why organizations aspire to capitalize the power of AI for HR purposes, or inversely, why they rather remain disengaged in AI-enabled HR practices. To comprehend this, subjective experiences, concepts, visions, and beliefs are studied (Silverman, 2020). This requires an in-depth understanding of the context that precedes people's experiences and beliefs (Myers, 2019). To allow for this approach, this research follows a qualitative nature (Myers, 2019; Silverman, 2020). Along with its qualitative nature, this research follows an exploratory design, as it attempts to develop attributions that extend the reader's acquaintance with the existing attributions related to generic HR practices in organizations (Stebbins, 2001; Swedberg 2020). This research travels over the HR field of study by examining HR practices under a new state of affairs: AI advancement in the HR discipline.

3.1 | Data Collection Method

This exploratory qualitative study follows the Grounded Theory Approach (GTA) as it is the primary objective to develop a theory based on the principal technique of inductive data analysis. This calls for a continuous interplay between the data collection- and data analysis phases (Bowen, 2006). Strauss and Corbin (in Bowen, 2006, p.13) indicate that a systematic collection and analysis is critical for deriving an inductive theory towards the phenomena of study. Allan (2003) indicates that studies following a GTA approach typically tend to pursue data collection by means of interviews. To gain an in-depth understanding of people's perceptions towards AI-enabled HR practices, semi-structured interviews are conducted in the data collection phase of this research. The rationale underlying this choice is two-fold. Firstly, semi-structured interviews assure that all subjects are asked the pre-determined questions that necessarily should be answered for the foundation of this research (Longhurst, 2003). This allows for a standardization of results across the various interviews that took place (Hull, 2013). Secondly, this data collection method facilitates the researcher to seek clarification and to directly anticipate the answers provided by the interviewees (Doody & Noonan, 2013). This enables the researcher to gain in-depth knowledge about various matters that would not have been considered talking about prior to the interview. As a result, the scope of this research is strengthened and new concepts emerge, which ultimately fits the exploratory aim (Doody & Noonan, 2013).

3.2 | Participants and Procedure

Research by Morse (2007) emphasizes that careful and purposeful sampling is crucial for the quality of data collected. Respondent selection within this research is therefore subject to non-probability sampling techniques such as purposive- and snowball sampling (Acharya et al., 2013; Hull, 2013; Morse, 2007).

The sample had to comply the norm of selecting people in specialist- and managerial functions in HR parts of technology. These people either had to be involved in the decision-making process towards the adoption- or rejection of AI-enabled HR software solutions at Dutch organizations or had to be working on a daily basis with- or for these software providers of AI-enabled HR solutions.

Based on these criteria a sampling frame was retrieved and people were contacted via LinkedIn or via e-mail to invite them to participate in the research. The rationale for inclusion was two-fold. First of all, decision-makers that recently engaged in the adoption- or rejection of AI-enabled HR software solutions were incorporated for three reasons. First, to retrieve their current demands for AI-enabled HR software solutions. Second, to identify their perceptions towards AI-enabled HR practices. Third, to derive explanations on the willingness to adopt or intent to reject these AI-enabled HR software solutions. Second of all, specialists- and managers in HR parts of technology, from the Netherlands and the United Kingdom, were consulted to become informed on the development of AI in the HR software solution service industry. They were moreover contacted to retrieve the current HR demands in the market and to evaluate these against the AI opportunities- and limitations they envision. The specified criteria and explicit rationale for inclusion reflect that purposive sampling was in place (Hull 2013; University of Twente, 2021). With the purpose of enlarging the sample size, the respondents participating in this research were asked whether they knew other suitable candidates for this research. Obtaining and selecting respondents via this matter complies with the snowball sampling procedure (Hull, 2013; University of Twente, 2021). This approach has resulted in a total of 14 interviews which have been conducted with 14 different respondents of which the interviewee profiles are represented in Table 2.

Table 2: Interviewee profiles

Interviewee profiles
Regional Sales Director
Project Leader Human Resources
Chief Human Resource Officer
Digital Transformation and Program Manager
Human Resource Officer
Chief Human Resource Officer
Product Manager
Human Resource Director
Future of Work Strategist
Human Resource Analyst and Coordinator
Business Consultant
Principal Consultant
HR Manager
Project Leader Human Resources

Prior to the data collection, the ethical committee approved this research (nr. 221190). The interviews were conducted either virtually through Microsoft Teams or personally at the organization's office. The average duration of the interviews was 73 minutes. Before the start of the interview, the interviewees were informed about their anonymous participation and the option to withdraw from the research at any point. Participants were assured that the obtained data only serve academic purposes and that none of the research results could be traced back to its source, either the participant or the corresponding organization. Verbal consent for participation in the research and the recording of the interview was requested at the beginning of the meeting. This decision was made to facilitate an effortless procedure for the participant before the interview took place. Concerning regulations of data storage, the researcher informed the interviewees that they would receive the transcript for approval within two weeks. Once approval was obtained, the interview recording was deleted. The researcher prepared standardized questions, but due to the differentiating profiles and experiences of the interviewees, the researcher also developed tailor-made questions for each interviewee. To strengthen the validity, the interviews conducted in the first phase of this research served as input for the evaluation and development of the interview questions for the second round of interviews. This fostered the clarification of questions and assured that the questions asked would indeed capture the answers the researcher was seeking, fostering the validity of this research (Golafshani, 2003).

3.3 | Data Analysis

In the analytic process of examining- and coding the obtained data, additional questions that required answering were formulated. This was done to avoid assumptions and to extend the understanding of certain topics or phenomena. Before the interviews, respondents were already informed that the transcript sent for approval could include some additional questions for clarification. This method has cultivated clarification on ambiguous responses and allowed respondents to think about questions they initially could not answer, enhancing the credibility of this research (Tobin & Begley, 2004). This process relates to the theoretical sensitivity the researcher employed (Hull, 2013; Vollstedt & Rezat, 2019). According to Charmaz (2006), this also assists in asking the right questions such that the data reveals what lies beneath the surface. This grants the researcher a thorough understanding of the phenomenon under investigation and allows insights to emerge (Hull, 2013).

The interviews were initially transcribed by means of two distinctive software programs. An automatically generated transcript was derived from the interviews that were conducted via Microsoft Teams. The timestamps were eliminated, and the transcripts were manually revised for corrections. The interviews that were conducted in person, were recorded by a mobile phone and tablet. The audio recording was inserted into AmberScript and subsequently manually revised for corrections. The approved transcripts were manually coded on paper. This data analysis method was preferred because it provides the researcher the opportunity to easily visualize, by means of drawing arrows and figures, data pieces that could be linked to each other during the coding process.

As this research explores HR attributions towards the adoption- and rejection of AI-enabled HR practices, inductive coding is preferred. The data analysis process was therefore not characterized by a pre-defined coding scheme as the attributions in current literature do not fit the context of AI integration in the HR discipline. While analysing the data, codes were developed through open-, axial-, and selective coding following Strauss and Corbin (in Vollstedt & Rezat, 2019, p. 86). This inductive approach allows themes, patterns, and categories to emerge which fosters the evolvement of attributions specifically related to the context of AI and HRM (Bowen, 2006). With the aim to inductively develop a theory on the attributions people hold towards AI-enabled HR practices, a Grounded Theory Approach (Bowen, 2006; Hull, 2013) with a constructionist paradigm is applied (Levers, 2013).

The coding process entails that the obtained data is firstly broken down, secondly conceptualized, and thirdly re-assembled (Hull, 2013). The first step refers to open coding in which the researcher examines the category and concerns addressed (Hull, 2013). The purpose of open coding could be referred to as deciphering and fracturing the identified categories (Hull, 2013; Vollstedt & Rezat, 2019). The extensive number of codes generated requires a second-order theme. This represents a theme under which the open codes are collected. The axial coding purpose is reversed to that of open coding, as it aims to reassemble the data in novel ways (indicating the coding paradigm) (Hull, 2013; Vollstedt & Rezat, 2019). By means of selective coding, the codes are narrowed under an aggregate dimension, which reflects the process of axial coding. This process requires a higher degree of abstraction (Hull, 2013). Throughout the coding process, the researcher travels between the three types of coding. Eventually, by linking categories and establishing connections through themes and aggregate dimensions, a theory emerges (Levers, 2013). Throughout this data-analysis process, it appeared that respondents employed at the same organizations provided similar answers to questions specific to the organizational demands of AI-enabled HR practices and the process of adoption or rejection. This signifies a certain degree of reliability regarding the interview questions.

4. | RESULTS

This chapter familiarizes the reader with attributions explaining the willingness towards the adoption- and rejection of AI-enabled HR practices. The attributions presented in this chapter emerged from the inductive coding process. The coding schemes that visualize this process are included in Appendix I. The concepts and themes derived from the data analysis are composed into an aggregate dimension: an attribution. As specified, an attribution is formally defined as "the act of saying or believing that something is the result of a particular thing" (Oxford Learner's Dictionaries, 2022a). This chapter therefore explains where the willingness towards AI adoption- and rejection results from. Thereby, it zooms in on contextual factors and internal beliefs-, convictions-, concerns-, and fears associated with AI-enabled HR.

4.1 | Attributions Concerning the Adoption of AI-enabled HR Practices

This section identifies the internal- and external attributions concerning the adoption of AI-enabled HR practices. It explains where the intent and desire to integrate AI into the HR discipline results from. The internal attributions are presented in sections 4.1.1 up to and including 4.1.4. Section 4.1.5 explains the external attribution.

4.1.1 | Autonomous Career Mapping

The intent to integrate AI in the HR practice of training and development stems from the disbalance between HR's controlling- and commanding approach and the urge for empowerment of the new generation of employees. Generation z employees call for an increased extent of independency from superiors in determining development pathways to pursue their career aspirations. Respondents acknowledge that this is predominantly shaped by their expectation to receive tailored development needs and training opportunities aligned to their personal ambitions. Currently (HR) managers however fall short in providing employees with personalized training opportunities that serve the interest of employees rather than desired business outcomes. This is because the allocation of training- and development opportunities is nowadays dominated by bias. First, (HR) managers tend to strategically position a particular employee according to their own preferences. As a result, they could either consciously or subconsciously initiate training opportunities they consider to be a match for that position. Secondly, they tend to recommend training options that have been proven to be successful and to be valued by other employees, leading to generalized development opportunities.

"Currently he must talk to either his manager or HR about good training possibilities. And then HR or that manager always has a function in their minds in which they would most likely position that employee. Moreover, this HR professional or manager also has his own preferences because he knows, based on other employees who have already completed specific training opportunities, the 'high quality' training programs. However, this excludes a very large number of other reviews that could have been considered for training opportunities. And it is exactly that bias that you eliminate when the employee takes on the ownership. […]

I want something with my job, and concerning employee self-service this is me, this is my profile. And then I could ask the system what my training needs would be. And then you have, you know, an intelligent system or at least definitely a 'cloud based' system. Then you could say, well go look that up for me on the World Wide Web. But that is of course, in my opinion that is where we should be heading, and I think that is only really AI." – [Respondent 3]

Respondents insist that the profound influence of bias and the impersonal approach to the allocation of training opportunities, resulting in generalizations, ought to be diminished by adopting AI-enabled employee self-service tools. They are convinced that AI empowers employees to autonomously convey their ambitions, not being shaped by, or translated into organizational desires or needs. The willingness to adopt AI is therefore attributed to the belief that AI-enabled employee self-service tools can overcome the human impotency in transferring learning ownership to employees by eliminating the principal source of bias. Moreover, respondents consider AI capable of identifying personal performance metrics (i.e., indicators recognized as representative for evaluating employee performance against their ambitions), and objectively analysing performance data to identify training needs aligning with the employees' ambition. Respondents therefore acknowledge AI as a crucial pillar in constituting personalized training opportunities based on individual career aspirations. AI adoption is therefore ultimately perceived to harmonize HR's willingness with capabilities that enable new generations of workforces to autonomously map their career.

4.1.2 | Self-governed Job Crafting

It appears that the optimization of workforce capabilities is bound to escaping the conventional thinking that people should fit pre-scribed job descriptions. Organizations aspire to engage in job crafting to bridge the gaps between employees' competencies and outstanding tasks. This desire is however transferred into an undeniable necessity by the tightness of the labour market which challenges organizations to do more with less. This labour market tightness is related to job crafting as it forces organizations to shift the focus from hiring new employees to rather engage in unveiling unknown competencies of the existing workforce to complete outstanding tasks. Where HR professionals could set a change in motion, it is argued that they cannot 'make the picture complete'. They do not have the capacity to identify, for an entire workforce, where tasks should be released or added such that it complies with both, employee competencies and job demands. AI is recognized as the change enabler to facilitate job development due to its analytical capabilities that fuel data-driven suggestions on job enrichment- and task rotation opportunities. The desire to leverage AI is explained by the discrepancy between HR's willingness and capabilities to advance the match between pre-determined tasks that require novel strategic positioning and employees' competencies. Favouring AI adoption is according to the respondents attributed to the belief that merely AI can constitute an optimal win-win situation. AI firstly 'makes the picture complete', assuring that outstanding tasks are fulfilled. AI secondly enables employees to exploit competencies that were not featured before (i.e., because organizations were not aware of specific employee capabilities), which facilitates job enrichment. Unlocking these competencies for business purposes represents the core of the attribution of self-governed job crafting. Employee ownership in this process stems from the voluntary action of linking one's LinkedIn profile to the already available employee data to stimulate the unlocking of 'unknown' competencies.

"Let me call it like this, I think it provides additional dimensions to data that we as humans cannot interpret. There is so much data available that you as a human being are not able to put it all together. And I think that an application can bundle a lot of information and subsequently provide advice." – [Respondent 1]

"The operator working with this machine, and doing this incredibly well, is probably also a secretary at a football club who is also doing very smart things there. And because we do not know this, we presume he does not possess these competencies. And I think by means of AI, by means of more information, you can enable people, via employee self-service, to link their online profiles to their employee data, which allows us to gain a better understanding of their total competence package. […] As long as the machine stays the same, the job of the operator stays the same. But if somebody acknowledges he wants more, then that could become a very weird conversation, compared to if somebody grants you access to all this data, which is of course a voluntary action. So, you are not only talking about talent development, but you are also talking about job development. We could talk about the jobs we already have, but I start to believe much more in job crafting and its development. […] I also think that AI enables you, in terms of job crafting, to say, what if I add something here, and release something there, I can still make the picture complete, something that I cannot say." - [Respondent 3]

4.1.3 | Sustainable Employability

The Covid-19 pandemic has initiated renewed workforce priorities pertaining to employee well-being and employee flourishing. Respondents address that concerning employee well-being the importance of workload- and work-life balance has been elevated. These determinants were under significant pressure amidst the Covid-19 pandemic; personal and private lives became increasingly intertwined (i.e., hybrid working) and the extreme workload in certain sectors (i.e., healthcare) was detrimental to employees' work-life balance. The call for lower workloads and work-life balance stabilization has ever since prevailed. Respondents however experience that HR cannot live up to these renewed workforce priorities, especially not in this tight labour market in which organizations are challenged to do more with less. The current tight labour market thus not only reinforces the urgency of employee well-being but also puts it under pressure again. What specifically frustrates respondents is HR's impotence in releasing this pressure. The absence of grounded predictions on burn-out-, absenteeism-, or turnover risk impairs the possibility to avert preventable employee turnover. Respondents experience this as particularly burdensome in times of persistent workloads and constant work-life balance disruptions. The conviction attributed to the adoption of AI therefore entails that unexpected workforce developments that ought negatively to impact the workforce's workload- and work-life balance even further, can be better prevented. It appears that the pressure on the workforce could be released when AI systems initiate warnings about predicted personnel shortages which organizations could timely anticipate. The AI technology could be deployed to automatically retrieve and indicate when employees are expected to retire, as well as to derive from the language and expressions used in employee communication (i.e., e-mails) whether someone is a potential burn-out-, absent-, or turnover risk.

Rather than performing such analyses, HR professionals are expected to proactively act on AI-initiated warnings to timely diminish and prevent these risks. AI is expected to diminish the constructive and continuous labour shortages and scheduling demands by initiating a proactive and preventive approach to performing the HR practice of strategic planning. The inclination to deploy AI in a supportive matter therefore resides in its extraordinary analytical capabilities that generate data-driven predictions on which HR could proactively and preventively act. Whereas the reduction of sudden and unexpected turnover is likely to release workload pressure, the preventive approach is also expected to positively contribute to employee health by means of burnout prevention. Respondents finally recognize that the predictability of turnover risk gives rise to the proactive initiation of internal mobility options to avoid this. The latter simultaneously covers the concept of employee flourishing.

"Because with the capacity queries, getting schedules closed is a hell of a job. You affect the schedules and the work-life balance of our people, and they all think something about that. […] Please note, you run a risk here because the data from the past indicates that there is turnover and that your absenteeism will increase in the month of October. I just name something. That we have a group of retirees, and we can combine that data, so we know that we need new staffing then. Until indeed, when is there Artificial Intelligence? If you are proactively approached by things." – [Respondent 4]

Respondents emphasize that the pandemic has shifted perceptions towards the function of work in our lives. Concerning employee flourishing, respondents specifically address that the aftermath of the Covid-19 pandemic has brought to light the increased importance of job happiness and satisfaction. This is associated with the prevalent desire of people to get meaning out of their jobs and their increased interest in lifelong learning. Placing full responsibility on the shoulders of (HR) managers in safeguarding this exposes their shortcomings in being able to provide every layer of the workforce with equal flourishing- and learning opportunities. AI is identified as a remedy for this human limitation. The willingness to adopt AI is therefore attributed to the belief that AI's impartialness is expected to allow everyone to pursue a sustainable joyful career no matter their age, performance, or relationship with managers.

Respondents stipulate that AI-enabled skill-based matching constitutes transparency and equal learning opportunities to the workforce. Another positive connotation attributed to AI adoption is the trust in its synergy between pro-active and real-time initiation of flourishing opportunities. This reflects a pro-active approach on both, creating and maintaining employee happiness. By adopting AI, HR 'kills two birds with one stone'. They do not only release unnecessary workload pressure in this tight labour market, therefore positively contributing to work-life balance. They also anticipate the highly prevailing needs of employees to get meaning of their jobs and seek opportunities to flourish.

"And um internal, you know gigs that I can do where yeah, I have my day job know, but what I am really interested in and passionate about is this over here? I could do that inside of my company and maybe make a little extra money or contribute in some other way. So again, I think that is where AI can also play a role in saying hey, I am scraping information about you and I have got this little side gig thing. If you are interested, it would be really cool." – [Respondent 8]

"Suppose you turn 55 and that, based on a personalized employee portal, one could ask this employee whether she or he would like to invest time in the onboarding process of new employees. Well in that way I think if you are going to register what people have done, that could serve as valuable input on how you could coach and steer others to remain happy in the right position. Because I think that theme will remain topical." – [Respondent 9]

The current tight labour market points to the inescapable conclusion that anticipating these renewed workforce priorities is inevitable. A fully human approach to this would do more harm than good. The willingness to adopt AI is therefore attributed to the conviction that this could facilitate the transformation from a reactive intuitive discipline to a preventive data-driven discipline that safeguards these novel priorities. This AI technology would not only allow supporting human decision-making, but it could also replace HR professionals in performing repetitive and administrative tasks. This is imperative as respondents explicitly invoke the shortcoming of HR professionals to focus on human value creation due to their accountability to solve 'low added value' tasks. Increased importance is attributed to the perspective of forging authentic relationships with employees. Respondents feel that this is particularly important in order to remain personal in a prospective technologically dominated HR. Ultimately, AI is expected to sow the seeds of the preventive strategy which HR should subsequently proactively execute to account for a continuous happy- and healthy career.

4.1.4 | HR Optimization

The need for HR optimization is thriving as the topical debate on inclusion and diversity demands inclusive workforces. Furthermore, the labour market tightness calls for sustainable employee relationships. It is argued that optimization can be achieved by enhancing service quality and/or reducing the costs of the HR practices performed. Respondents dedicate explicit mentioning to the optimization of the recruitment- and selection practice as they recurringly stress the importance of establishing a diverse- and inclusive workforce. They however do not believe that this is achievable when the hiring practice is subject to a fully human approach. This stems from the conviction, resulting from respondent experiences, that we naturally choose people that suit us. Whereas this obstructs workforce inclusion and diversity, it is also perceived to be detrimental to long-term employee relationships and to the service delivery of an organization. This is perceived as candidate selection is not primarily based on a fit to the organizational needs.

The preference for AI adoption is attributed to the belief that AI is indisputable in constituting a reliable hiring practice that simultaneously facilitates a predictive and more objective approach. Respondents argue that the hiring process ought to become evidence-based through AI's support. AI could be deployed to run data analyses and compose high-performer profiles according to which benchmarking criteria are constituted. Subsequently, by conducting personal assessments without human intervention, AI could objectively evaluate the match to benchmarking criteria and predict the probability of success of a candidate. AI is perceived as indispensable in facilitating increased objectivity to constitute a 'fairer' practice in terms of inclusion. The predictive approach is furthermore considered imperative in the current tight labour market where the importance of long-term employee relationships is more apparent than ever. Moreover, predictive hiring would also allow for cutting costs in the intensive hiring process. The conviction attributed to AI integration is that an impartial, data-supported selection leads to hiring that cultivates candidates that tend to stay longer with the organization. This diminishes (early) turnover costs.

"I think the positive thing is that you can be more predictive of course. That, without bias, without prejudice, you can perform certain processes, such a recruitment and selection, much better. Using AI, you can better select, which diminishes absenteeism and turnover. This is because you recruit on specific criteria, criteria which have been demonstrably proven that the right candidate is selected for the right job." – [Respondent 4]

Respondents repeatedly emphasize that the optimization of the performance of HR practices is also reliant on the resources and permission granted by management. Their experience learns that data should be presented to management to obtain their approval on optimization initiatives. Respondents' positive stance towards AI adoption stems from their perception of AI being an ultimate business partner to constitute this. AI's analytical capabilities combined with its predictive power would allow HR to engage in data-driven scenario thinking. AI adoption is favoured as it creates the opportunity for HR to present management with data that can substantiate the relevance of optimization initiatives over time and over different scenarios. The willingness to deploy AI is therefore also attributed to the belief that AI can finally provide HR with the proverbial seat at the management table HR is pining for.

"So, I think that as HR you must think much more in scenarios. Artificial Intelligence could serve as a business partner in information interpretation. […] Again, your approach is much more data-based, so that helps the director make choices that may be very different from the initial vision but are more reflective of the human perspective. And then you have obtained your seat at the management table, then you could really be a part of the management. If you say, dear HR director, we have a workforce that is aging so much in the upcoming five years, that we will face huge employee turnover in five years. I think we should now focus on rejuvenation because otherwise we have a problem. The director will say, wow, please provide me with more information." - [Respondent 1]

4.1.5 | Contagion Effect

From the data analysis it appears that the main argument for AI integration in HR practices could also come from outside the organization. Respondents feel that AI adoption is becoming a trend. They initiate that if one enables HR practices by AI, others are naturally expected to follow. This addresses an extrinsic motivational factor. Respondents believe that at a certain point in time, organizations simply cannot lag behind regarding AI adoption and could succumb to external pressure. The willingness to adopt AI is therefore attributed to the pressure that is experienced in having to conform with institutional norms in keeping up with technological advancements as AI.

"Of course, it is not just about what you want as an organization, but you also have the environment around it, do you not? And I think that is also very important. And I think it is also a kind of a contagion effect that if one joins, you must follow." - [Respondent 2]

4.2 | Typology of Attributions Towards the Adoption of AI-enabled HR Practices

The typology matrix presented in Table 3 shows the overall classification of the attributions towards the adoption of AI-enabled HR practices. The differences between internal- and external attributions, employee ownership- and organizational ownership, and a strategic employee centric- and a strategic business centric approach are explained in Appendix II. Appendix III subsequently elucidates the position of the attributions in the typology matrix of AI adoption.

Table 3: Typology of attributions towards the adoption of AI-enabled HR practices

Typology of attributions towards the adoption of AI-enabled HR practices

	Internal attributions		
	Strategic employee centric approach	**Strategic business centric approach**	**External attribution**
Employee ownership	Autonomous career mapping	Self-governed job crafting	Contagion effect
Organizational ownership	Sustainable employability	HR optimization	

4.3 | Attributions Concerning the Rejection of AI-enabled HR Practices

This section identifies the internal- and external attributions concerning the rejection of AI-enabled HR practices. It describes where the aversion towards the integration of AI in the HR discipline results from. The internal attributions are presented in sections 4.3.1 up to and including 4.3.3. The external attributions are described in sections 4.3.4 and 4.3.5.

4.3.1 | Distrust

The willingness to reject AI-enabled HR practices stems from the desire to hold on to established perceptions employees have of HR. Specifically, to hold on to the belief that employees can trust HR. From the data analysis, it appears that the digitalization of HR practices already goes hand in hand with questions and concerns related to the accessibility and usage of employee data. The critical determinant fuelling these discussions is that employees do not really know anymore what is happening. This harms their trust. Undermining the trust of employees is a recurring concept that also pertains to the opacity algorithmic decision-making could bring into existence. Respondents argue that if employees lack understanding of how decisions are being made (i.e., algorithms are too complex and difficult to understand), they will mistrust the AI system as they do not know for which purposes their employee data is used. This matter could be resolved by openly communicating the parameters on which the decisions are based. Yet, the fear respondents attribute to AI technology relates to its complexity. When AI is too complex to grasp, it infringes the organizational responsibility in either explaining or validating AI-enabled decisions. The perceived complexity of AI combined with respondents' current experiences with employees proactively questioning data-processing procedures, constitutes fear of employee distrust. The urge to prevent distrust, not only in AI but even more importantly in HR, is attributed to the intent to remain disengaged in AI-enabled HR practices.

"When you have these AI algorithms that are difficult to define and describe, and to articulate the people about how these decisions are made, once again it causes people to mistrust the system, mistrust the data. So, it is a delicate balancing act again." – [Respondent 8]

"I think the danger is that it is so complex, that nobody anymore understands how a decision was made. And yes, then you are not able to test or validate whether it is correct." – [Respondent 6]

"Now employees really feel that they could trust HR because they know what is happening. But almost every week I have the discussion of okay: where is that data and who has access to all that data, to all salary data right? Are you going to use that data and where will it be located and how will it be used? I think that is the biggest consideration which also makes it very complicated." – [Respondent 12]

4.3.2 | Quality Impairment

AI is not only perceived as a holy grail for HR. Some respondents explicitly call into doubt the positive influence AI will have on the quality of HR practices. They express their worries that the human dimension of HR will be put in jeopardy when HR processes are becoming too reliant on AI. Nevertheless, it is this human element that is positively associated with HR's reputation of being a safe haven. Respondents claim that too much AI reliance will impair the critical thinking capacity of HR professionals due to which too little attention will be paid to whether things are going as they should. The danger attributed to this is that HR professionals presume that things go well which could withhold them from engaging in personal employee conversations. Respondents are afraid that this will negatively impact the quality of HR practices as it is precisely these personal conversations that bring forward what is going on in an organization and that allow one to not only anticipate, but also identify people's emotional needs. Being too reliant on AI cultivates negative perceptions towards AI adoption, as respondents attribute this to insensibility in the HR practice. These negative tendencies regarding AI adoption appear to turn into decisive rejections if AI retains more control than HR professionals in the strategic performance of HR practices. Specifically, the fears of exclusion, datafication, and diminished human-sense making are attributed to rejection. Respondents address that this would obstruct the possibility to look with care and empathy at the workforce, invest in genuine relationships, identify and respond to people's (emotional) needs, and detect undesirable developments and anticipate these. These fears predominate the decision-making process and fuel the willingness to reject AI-enabled HR practices through AI automation to prevent quality impairment. Respondents specifically aim to safeguard the 'human element' accounting for the personal approach in HR as, according to their experience, this has cultivated employees' perceptions of HR being a safe haven.

"But I think it is more aligned with the reputation of HR. HR is of course perceived in many organizations as impartial and as a safe haven. […] But at the moment your data is being used for whatsoever, is that not inconsistent with the reputation and role you have as HR within an organization?" – [Respondent 12]

"As far as I am concerned, it could be a danger that certain things (think of information that needs to be registered and processes to be automated) are too much based on AI so that the people themselves will no longer think. In the field of HRM, you are still dealing with people that are being employed by the company. People with emotions. So, if processes, and for instance HR professionals rely too much on AI, you run the risk that too little attention is paid to whether things are going as they should. Perhaps it is after all assumed that things go well." – [Respondent 7]

Quality impairment of HR-practices is not only bound to AI automation in decision-making. AI augmentation also leverages concerns on quality impairment in specifically small and medium-sized enterprises (SMEs). Respondents foresee problems with AI adoption in terms of the objectivity of outcomes and the narrowness of data input. Whereas positive perceptions are adhered to HR optimization in recruitment and selection based on benchmarking criteria, respondents perceive challenges in safeguarding the reliability and representativeness of these parameters. These challenges are especially prevalent at SMEs rather than at large corporates (i.e., banks). Respondents are hesitant about AI adoption, with the purpose of making AI-supported decisions and predictions based on 'best practices' (i.e., success probability evaluated against high-performer profiles), in SMEs. They belief that despite the intent to optimize HR, AI will do more harm than good concerning the quality of the performance of HR practices. They are concerned that performance will rely on unjustifiable and unreliable parameters. These convictions are subsequently attributed to a potential rejection to AI-enabled HR practices in SMEs.

"You know, it is the quality of AI. And then I mean the quality in terms of whether it is coherent to HR? And especially the data output, is that really objectifiable? I am hesitant about this. I think that is the biggest challenge, also for AI." – [Respondent 3]

"An important problem with that is according to me also the technical development. Suppliers are so to speak shouting from the rooftops, but they have very little yet. And I also think that customers really are not quite there yet. Look, if you want to develop an algorithm you should know on the basis of which parameters you want to do this. Which variables are going to determine, whether this is it or not? Netflix for instance can rely on all its users. Yet, with HR it is quite narrow, right? With HR we are obviously not talking about a world population. We do now have data on all employees from all over the world or anything like that." – [Respondent 10]

4.3.3 | AI Readiness

The aforementioned attributions explain why organizations capable of adopting AI in the HR discipline would still reject doing so. Nevertheless, the willingness to reject AI also results from the current inability to integrate AI into HR. From the data analysis it became clear that merely one out of the five organizations that recently engaged in adopting new HR software solutions is making use of AI features in HR. One by one, respondents attributed this to the organizational lack of AI readiness. According to them, there is a prevalent discrepancy between AI-enabled HR and the current prevailing HR demands. They experience that the current HR demand is primarily about realizing one central software solution that optimizes HR workflows. These current demands for one IT landscape on HR reflect how the infrastructure of HR software solutions is still far away from being equipped for AI-enabled change. Respondents attribute this to their perception of HR as the most reactive and slowest profession to be open to technological advancements in general. Pertaining this to AI, this also ought to result from the current abstract supply and lack of success stories that refrain people from understanding what it exactly entails. Whereas rejective stances towards AI previously resulted from fear and worries that shaped prevention, it is now simply attributed to the lack of AI readiness.

"No customer right now is saying: I need Artificial Intelligence. Because they are not there yet, you know. If they already know what it is. And how do you know you want it? Yes, I may have kept up with the times, but for what do I need Artificial Intelligence? I would not know that either. So, to speak, you only know that if you also know what it entails. And I think that people do not have that knowledge yet. People in general, unless you speak to someone who is into it." – [Respondent 7]

"I think again there is just generally speaking a perception that it is more buzz words than reality. If you really scratch under the surface, there is not a lot there." – [Respondent 8]

"We currently have a very fragmented software package, there are small pieces everywhere. Most of it is very old, which requires that you have to insert the same data in many places which increases error sensitivity. Since we are a multinational we wanted to work with a prominent provisioner because we really want a package that can also be used for the foreign countries, because otherwise we keep registering everything in separate systems."– [Respondent 6]

4.3.4 | Algorithmic Exclusion

The viewpoint on replacing humans with AI in decision-making has already been captured. However, it has not been evaluated in the context of an external attribution. Whereas organizations ought to control how they would like to deploy the AI technology, they cannot determine how the algorithms integrated into AI-enabled HR software are being developed. Yet, driven by the topical debate on inclusion and diversity they do have a clear perspective on this as they emphasize the relevance of a diverse and inclusive group of algorithm engineers. Respondents consider this paramount as they expect all algorithms to copy the ideas, norms, and values of people developing them. The less inclusive and diverse the algorithm engineers, the less inclusive and diverse the outcome. Respondents explicitly indicate that this does not necessarily mean that we cannot collaborate with AI anymore in the HR domain. However, this cultivates a specific rejection towards AI-enabled HR practices in the light of AI being decisive. The representativeness of the algorithm in place, in terms of diversity, cannot be identified nor controlled. Respondents address that this marks the importance of being cautious towards AI deployment. They fear that AI automation in decision-making gives rise to algorithmic exclusion as the presumed lack of diversity in algorithms is reflected in the workforce. It is nevertheless exactly this diversity that has been conveyed to become fostered by means of AI. As the fear of algorithmic exclusion is solely attributed to AI automation in decision-making, the intent to reject only prevails when AI is, rather than humans, in decision-making control.

"And yes, I do think that a risk inherent to algorithm development, is related to the fact that this development is initiated by people with their ideas, and yes, norms and values, right? […] I think when you look at the theme of inclusivity and diversity that it is very relevant that algorithms are developed by a diverse and inclusive group. In all levels, so age, gender, culture, it should be a diverse group composition." – [Respondent 9]

"So, I would really like to talk about that exclusion principle. When do you make it work for you? And when does it work against you, right? So, when does it decide? So, for me, it is mainly about the inclusivity that I think is very important."- [Respondent 4]

"What came to my mind is that when you look for instance at LinkedIn, depending on how you have completed your profile, some people appear often on top of your search results. […] But an entire legion, a really large group of people will not be found. That is quite risky because that does not always put forward, with for instance LinkedIn, the right people. And that should not be the goal, because it would mean that people who are smart with data, will be brought forward." – [Respondent 5]

4.3.5 | Commercial Data Exploitation

From the data analysis it appears that the deployment of AI systems goes hand in hand with employee concerns about data accessibility, data storage, and whether their data is used for the right purposes. According to the respondents, the biggest danger jeopardizing this data security is one organizations deploying the AI technology cannot control. Respondents appear to be apprehensive towards software providers safeguarding employee data security. They insist that the pressure that rests on the shoulders of commercial HR software providers is all about making money. Data is stipulated as a crucial asset that could enhance innovation in businesses, improving their market position. The commercial HR software providers have the data, can deliver this, but will they do that? That is the question and simultaneously the risk. What is the balancing act versus making money and data protection? How do commercial HR software providers deal with this in a world in which both principles are paramount? These are not only the questions respondents ask themselves, but these are also the questions that respondents cannot answer. And they exactly designate that as risky: uncertainty. Respondents are worried that the exploitation of data is a temptation commercial HR software providers can barely resist. Depending on the persons in charge of the decision-making process (i.e., AI enthusiasts versus AI sceptics) this could be translated back to the rejection of AI-enabled HR practices. As it appears that uncertainty thrives fear among the respondents, it could be said that the intent to ultimately reject AI adoption is attributed to the fear of commercial data exploitation.

"But I am 100% sure that at the moment you are innovating as an organization, and you have access to a bunch of data, but you cannot use it. You must be really persistent do you now want to think, let me use this data to run a little test." – [Respondent 3]

4.4 | Typology of Attributions Towards the Rejection of AI-enabled HR Practices

The typology matrix presented in Table 4 represents the overall classification of the attributions towards the rejection of AI-enabled HR practices. Appendix IV clarifies the positioning of the attributions in the typology matrix of rejection.

Table 4: Typology of attributions towards the rejection of AI-enabled HR practices

Typology of attributions towards the rejection of AI-enabled HR practices		
Internal attributions		
Strategic employee centric approach	**Strategic business centric approach**	**External attributions**
Distrust	Quality impairment	Algorithmic exclusion
	AI readiness	Commercial data exploitation

5. | DISCUSSION

This chapter firstly takes a closer look at the meaning and relevance of the results in light of the research question. The theoretical implications and practical implications are subsequently discussed. Finally, this chapter ends with a discussion of the limitations of this research and the directions for future research.

5.1 | Attributions Towards AI-enabled HR Practices

The purpose of this study was to identify the attributions towards the adoption- and rejection of AI-enabled HR practices. Our findings build further on the work of Nishii et al. (2008) who developed a typology of five HR attributions explaining the perceived purpose of implementing generic HR practices. By exploring the construct of HR attributions in an AI-context, this study found that people attribute different emotions to AI-enabled HR practices than they do to generic HR practices.

The convictions and beliefs attributed to AI adoption are rooted in the necessity, to anticipate renewed workforce priorities resulting from the Covid-19 pandemic, labour shortages due to the tight labour market and the call for equal hiring- and learning opportunities stimulated by topical debate on inclusion and diversity. These findings anticipate the notion of Sanders et al. (2021) that there is a scope to develop a better understanding of the determinants of HR attributions in which the wider context should no longer be neglected. The forthcoming attributions concerning the adoption of AI-enabled HR practices are presented in the green circle in Figure 1. These are identified as: autonomous career mapping, self-governed job crafting, sustainable employability, HR optimization, and contagion effect. The first two attributions show how AI adoption empowers employees to take ownership of their own ambitions, development pathways, and job enrichment. This should foster their autonomy and conscious decision-making, which could be considered a surprising outcome as scholars thus far mainly associated AI adoption in HR to autonomy infringement (Charlwood & Guenole, 2022; Tursunbayeva et al., 2021; Tong et al., 2021). The three attributions of well-being, service quality and cost reductions, identified by Nishii et al. (2008), being integrated into two comprehensive attributions of sustainable employability and HR optimization reflects the seismic shift AI can and apparently should constitute: transforming HR from a reactive intuitive discipline to a preventive data driven discipline.

The red circle in Figure 1 presents the attributions concerning the rejection of AI-enabled HR practices. These are identified as: distrust, commercial data exploitation, quality impairment, algorithmic exclusion, and AI readiness. The worries about employee distrust and commercial data exploitation are attributed to AI adoption in general. The arrows in Figure 1 reflect that the rejective attributions of quality impairment and algorithmic exclusion merely prevail when AI automation of the HR practice is pursued. This perception is however not applicable for SMEs, where the intent of AI augmentation is also attributed to rejection. Although Raisch and Krakowski (2021) indicate AI augmentation to be the preceding step towards AI automation, this study emphasizes the rejective tendencies towards this notion regarding decision-making and strategic performance of HR practices.

The overlap between the green and red circle presented in Figure 1 indicates that the willingness to integrate AI in the HR domain is dependent on how AI will be deployed. This does not only identify AI automation in decision-making as the source of the paradoxical perspectives: AI adoption versus rejection, but it also reflects how the attributions towards adoption and rejection are interrelated.

In general, AI adoption is cherished because of AI's predictive power, analytical capabilities, proactiveness and contribution to impartialness. The conviction prevails that HR should exploit these features to overcome the human shortcoming in attaining objective data-driven decision-making, transferring learning ownership to employees, and establishing working conditions which safeguard the novel perspectives on employee well-being and flourishing. The willingness to exploit these AI features predominates as long as AI automation merely prevails in the performance of administrative tasks and HR professionals ought to remain decisive in strategic decision-making.

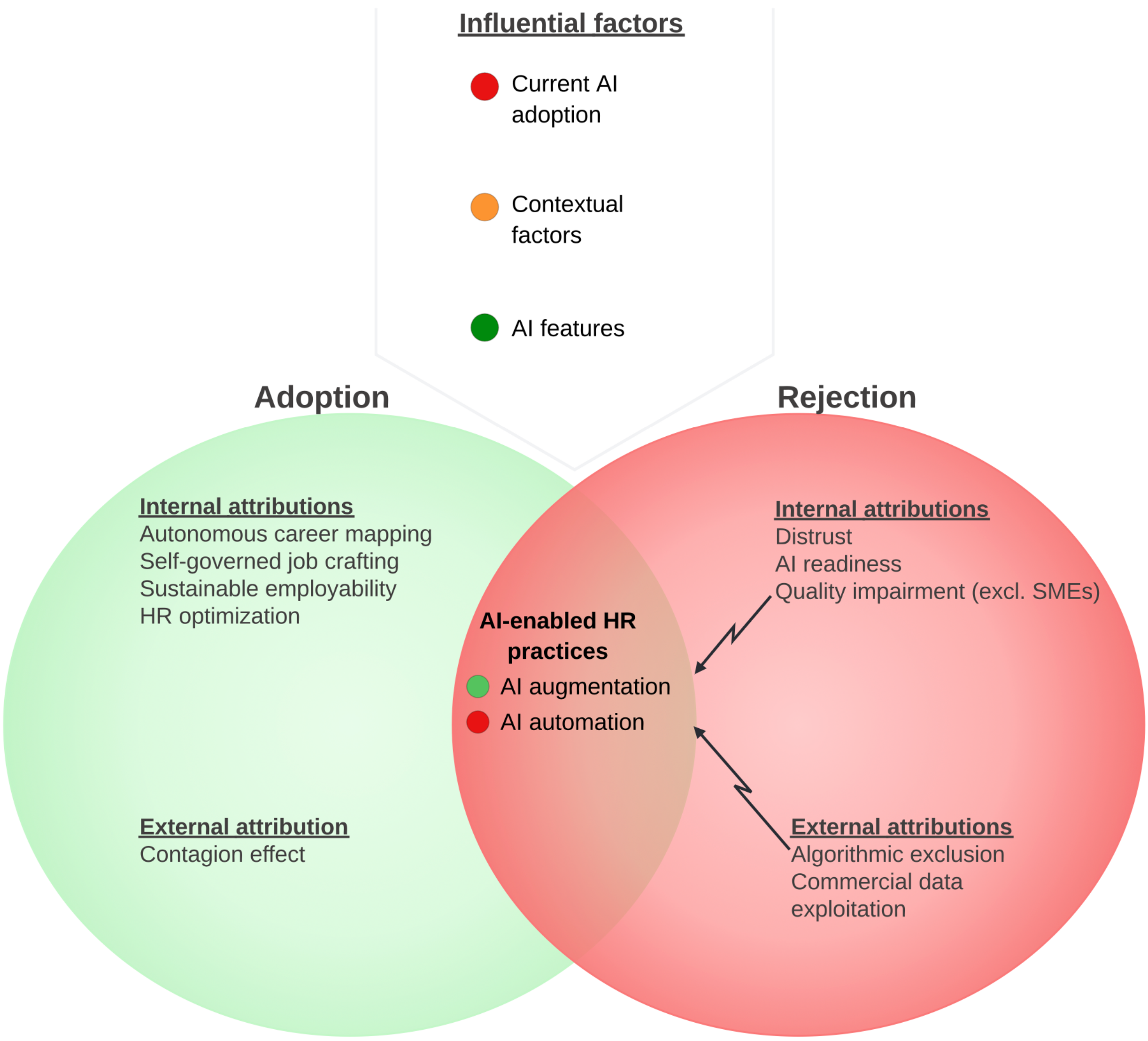

Figure 1: Visualization on the attributions towards AI-enabled HR practices

5.2 | Theoretical Implications

This study has several implications for theoretical developments regarding the HR attributional theory, HR technology research and SHRM research. By applying the HR attributional theory to the context of AI, different classifications emerge. Similar to the HR-attribution dimensions typology of Nishii et al. (2008), a distinction is made between internal- and external attributions and between a business- and employee centric approach. Rather than stipulating a difference between commitment- focused and control- focused attributions (Nishii et al., 2008; Özçelik & Uyargil, 2022), our results show a distinction between employee- and organizational ownership. A possible explanation for the emergence of this classification resides in the technological orientation of this research as this study focuses on HR attributions in an AI context. Rather than HR professionals being responsible for generic HR practices, our results show that there is a possibility and demand for employees to be in control of and responsible for the deployment of the AI system. This relates to generating either employee-centric (autonomous career mapping) or business-centric outcomes (self-governed job crafting). This suggests that organizations also appear to be dependent on employees consulting the AI technology for boosting the variety, volume, and velocity of data to attain more personalized decision-making. This furthermore implies the importance of investigating autonomy stances towards the adoption of prospective technological advancements in the field of HR. Our research therefore suggests the utility of focusing more future HR technology research on the way that AI-enabled HR practices are enacted in organizations, through employee- or organizational ownership.

Building further on the classification of ownership, the attributions of autonomous career mapping and self-governed job crafting address that the willingness towards AI adoption also resides in the employee empowerment that HR desires to initiate by means of AI-enabled employee self-service applications. Earlier studies by Charlwood and Guenole (2022), Du and Xie (2021), Turnsunbayeva et al. (2021), and Tong et al. (2021) suggested that AI adoption undermines the sense of autonomy through the continuous capturing of information. However, results of this research highlight that AI-enabled employee self-service tools are expected to positively contribute to employee autonomy. Following the interrelation between autonomy infringement and harmed job satisfaction by Tursunbayeva et al. (2021), the results of this research imply that autonomy enabled by AI thrives job satisfaction through objective- and personalized development opportunities that constitute job enrichment. Whereas the paper of Tursunbayeva et al. (2021) is a scoping review that included grey literature (i.e., tweets with an #ethics hashtag) this research involved people in specialist- and managerial functions in HR parts of technology closely witnessing and experiencing the needs of workforces. We believe that these positive perceptions about AI integration regarding autonomy indirectly invoke a practical desire that contributes to SHRM research by not only knowing what AI could enable (autonomy) but also what it could potentially constitute (job satisfaction).

There appear to be shifting perceptions towards AI's function in supporting HR. These shifting perceptions specifically prevail concerning AI's support to the HR practice of training and development and HR's focus on employee well-being. Kaplan and Haenlein (2019) and Tambe et al. (2019) suggest that the HR practice of training- and development should be fostered by AI to first and foremost serve business outcomes. Shaped by contextual factors, AI-enabled training and development in this research is nevertheless predominantly bound to an employee centric approach. The rationale for this is threefold. First, AI adoption ought to foster employee autonomy. Second, AI adoption ought to provide equal learning opportunities to the workforce through algorithm enabled skills-based matching. Third, AI adoption ought to stimulate the proactive initiation of internal mobility options. Whereas Ahmed (2018) suggests that AI is leveraged for detecting employee's well-being to identify determinants of poor work performance (business centric approach), AI adoption in this research is attributed to safeguarding employee's well-being and happiness in the function they perform (employee centric approach). These shifting perceptions could be explained by the time frame in which the literary works are developed. Whereas this research is performed in the aftermath of the Covid-19 pandemic, the other literary works date from the pre-Covid-19 era (Ahmed, 2018; Kaplan & Haenlein, 2019; Tambe et al., 2019). The aftermath of the Covid-19 pandemic has clearly brought to light renewed workforce priorities. These priorities are currently put under pressure again by the current labour market tightness, which only reinforces the importance of employee well-being and flourishing (sustainable employability). Our findings concerning the context shaping the attribution of sustainable employability may be informative for trying to disentangle this prevailing importance of employee orientation in AI's adoption in the practices of advancement, training and development, leave and attendance and strategic HR planning.

Whereas the purpose of the existence of generic HR practices is attributed to service quality and cost reductions (Nishii et al., 2008), these themes are also prevalent in the AI-context of HR attributions. They are composed into the single attribution of HR optimization as respondents indicate that AI is capable of simultaneously enhancing service quality while reducing costs (i.e., making HR practice predictive). It is however remarkable that respondents did not associate the self-learning capability of AI (Kaplan & Haenlein, 2019) to this notion. This suggests that a discrepancy prevails between knowing what AI is and being able to translate this to practical resolutions in the HR domain. These findings suggest the utility of synergizing strategic HRM and HR technology research to focus more on the alignment between strategic theoretical perceptions of technological advancements and their practical insights on application.

Evaluating the result on the external attributions towards AI-enabled HR practices, one might wonder why the contextual factors are not considered as external attributions. This is an important consideration, especially when having examined the works of Nishii et al. (2008) and Sanders et al. (2021) who clearly relate the influence of contextual factors to external attributions. Nonetheless, within our research the influence of contextual factors prevails regarding the internal attributions towards AI adoption. This study shows that the contextual factors are linked to the need of HR to perform their activities differently. Nevertheless, the preference to anticipate these renewed demands by means of AI adoption is a voluntarily desire. The context of Covid-19 is addressed as an example. The internal conviction on paying more attention to employee well-being and flourishing prevails. This conviction is aligned with the belief that AI can constitute this by overcoming humans' impotency in constituting a data-driven and preventive approach to HR. The eventual decision towards AI adoption lies within the control of an organization as its adoption is freely chosen based on one's intrinsic motivation.

Rather than merely covering the existence of HR practices (Nishii et al., 2008), this research does not only derive attributions towards the existence of AI-enabled HR practices, but also identifies attributions explaining the absence of AI-enabled HR practices. This approach complies with the notion that it is specifically important to make sense of situations when polarizing storylines prevail (Hewett et al., 2017; Willcocks 2020). Yet, these storylines however do not appear to be very polarizing, as AI adoption is extensively cherished as long as it is adopted in collaboration with HR. Although Raisch and Krakowski (2021) address AI augmentation to be the preceding step towards AI automation, the findings of this study suggest that in terms of decision-making AI should be supportive rather than decisive. Despite administrative tasks and decentralized decision-making (i.e., which candidate should be invited for a job interview) HR augmentation is rather the end station than the intermediate step in terms of final decision making (i.e., who to hire, fire, or promote). These findings address the question initiated by Haenlein and Kaplan (2019) on how AI and HR can peacefully co-exist. It also anticipates the work of Euchner (2019) by addressing how value should be created without losing the sight of people. This study suggests that although feeling AI is designed to maintain relationships (Huang & Rust, 2021), the importance of establishing personal relationships between HR professionals and employees only grows. Moreover, these findings offer strong support to the work of Curtis (2023) which indicates that even though AI is preferred over sole human decision-making, it is favoured that humans retain more control in decision-making. These rejective attributions-based perspectives suggest that HR must ensure that they have a clear picture of what the constellation of AI-enabled HR practices are intended to achieve, and whether this fits the frame of AI augmentation in decision-making.

5.3 | Practical Implications

This study provides practical insights for HR software providing companies, HR professionals, and decision-making units involved in the selection of AI-enabled HR software solutions. The findings are valuable for HR software providers as this research reflects the emotions end-users attribute to the integration of AI in the HR discipline. The willingness to integrate AI in HR generally prevails, as long as AI is adopted with the intent to automate administrative tasks and to support HR professionals in decision-making. Research shows that the transition from positive stances to rejective tendencies towards AI integration in HR is fuelled by the transition from AI augmentation to AI automation in decision-making. This creates awareness among HR software providers about when AI is likely to gain acceptance in the field of HR. Furthermore, these findings suggest that adoption is specifically preferred in the HR practices of recruitment and selection and training and development. The desire to integrate AI in recruitment and selection especially prevails as it is experienced that this stimulates workforce inclusion and diversity. It also appears that the tight labour market contributes to this preference, as an improved hiring practice ought to diminish (early) turnover (costs.) AI integration in training and development is also preferred as renewed workforce priorities call for employee ownership and the allocation of equal- and personalized learning opportunities. These findings are valuable to HR software providers to narrow their supply to specific HR practices deemed most promising and lucrative to integrate AI into. The findings also indicate that AI's analytical capabilities, proactiveness, predictive power, and contribution to impartialness are the features that HR needs to constitute a shift from an intuitive reactive practice to a data-driven preventive practice. In addition, AI-enabled self-service tools are considered extremely valuable in terms of granting employee ownership. Combining this to the preferred adoption areas, this contributes to the understanding of HR software providers on how AI could constitute most value for end-users. Thereby, it stipulates the indispensable features that should require most development. In terms of rejective attributions, this study addresses general adoption concerns of distrust and commercial data exploitation. This provides direction to HR software providers for developing measures to overcome these matters and to assure that end-users can trust the software and its adoption.

This research also brought forward comprehensive visions of how AI adoption could foster or impair the HR practices at hand. The findings simultaneously addressed that the functioning of these HR practices is critical to the quality of the overall service delivery of the company. This is a valuable conception that captures the strategic alignment between HR goals and business goals. For organizations in general, this emphasizes the importance to involve HR professionals in the decision-making process on (AI-enabled) HR software solutions. Finally, this research provides rich insights for HR professionals and organizational decision-makers involved in choosing new (AI-enabled) HR software solutions. This study provides direction to HR professionals in initiating optimization initiatives to facilitate change in HR to become increasingly resilient against instability. Furthermore, this research contributes to attained decision-making as it informs decision-making units on the concerns that should be critically evaluated with suppliers of AI-enabled HR software solutions during the selection process.

5.4 | Limitations and Directions for Future Research

In analysing the limitations of this research, three aspects need to be acknowledged. First, the results of this study appear to be, to a large extent, based on expectations rather than experiences. The findings of this study indicate that besides the HR practice of recruitment and selection, none of the other HR practices respondents elaborated upon appeared to be yet AI-enabled. This means that the attributions derived from HR practices other than recruitment and selection do not emerge from experiences but rather reflect expectations of AI-enabled HR practices.

Second, as attributions develop over time (Hewett et al., 2017), the identified HR attributions in an AI context are specifically representative of the timeframe in which this study has been conducted. The synergy between the rapid advancement of AI technology and the prevalent conviction that this technology is ought to be a diamond in the rough for HR, give rise to the expectation that the attributions of this research are soon to be based on experiences rather than expectations. In addition, whereas the attributions in this research are influenced by the context of a tight labour market, the aftermath of the Covid-19 pandemic, and the topical debate on inclusion and diversity, changing external circumstances could alter the viewpoint on the willingness to adopt or reject AI in HR. While being particularly exemplary for the current phase in which HR finds itself, the future relevance of this research will remain. The relevance would reside in the typology framework developed, which could be consulted as a framework to evaluate experience-driven attributions. Next, the relevance of this literary work could then reside in its value of having constituted expectation-based attributions in an era in which, at some point in time, no longer expectation-based but only experience-based attributions can be cultivated. This literary work could then serve as a foundation for evaluating whether the attributions based on expectations and experiences are aligned.

Third, one must be aware of the limited generalizability of results. Thirteen out of fourteen respondents included in this interview were employed in the Netherlands and shared their vision with having in mind the General Data Protection Regulation law prevailing in the European Union. Knowing that this legislation is not applicable to the United States and Asia, in which developments on AI are considered to be very progressive, this study cannot be deemed representative for AI-enabled HR practices in countries outside the European Union. Based on data saturation and inductive thematic saturation (Saunders et al., 2018) it can be stated that the results of this study would be generalizable for Dutch organizations that are not yet engaged in AI-enabled HR practices.

Directions for future research emerge, amongst others, from the previously acknowledged limitations. First, as it is indicated that attributions change over time, we hope that this study inspires new avenues of longitudinal research on HR attributions in an AI context. This would allow researchers to derive insights on the change of attributions and to which determinants this change can be allocated.

Second, building on the limitation of expectation-based attributions, research should be conducted on attributions that emerge from organizations having integrated AI in HR practices throughout the entire employee lifecycle. When this research would be conducted with the same organizations as the expectation-based attributions result from, the two studies could be compared with each other to derive similarities or differences that could be translated to either the outcomes the technology constitutes, the development of the technology, or the contextual factors. Third, whereas this research has extended the HR attributional theory of Nishii et al. (2008) to an AI context, this research has not related the intent of adopting or rejecting AI-enabled HR practices to employee performance in HR practices. Future research is encouraged to do so, as this knowledge on the interrelation between AI-enabled HR and employee performance could alter stances towards AI adoption or rejection in the HR discipline. Fourth, it would be valuable to evaluate whether the intent of adopting AI-enabled HR practices (i.e., to pay more attention to strategic matters) are also transformed into actual behaviour once organizations have deployed the AI technology in the HR discipline. Finally, it would be very useful to adopt a cross-cultural approach to determine how the laws- and regulations, ethics, and cultural norms and values shape attributions towards the adoption- and rejection of AI-enabled HR practices.

6. | RECOMMENDATIONS

Based on the findings of this research, several recommendations can be made to stimulate the strategic development of AI-enabled HR software solutions and to guide critical decision-making on the adoption of AI-enabled HR software solutions in HR. HR software providers are on the short-term recommended to not be put off by the current lack of AI readiness. The instability resulting from recent contextual forces means that HR acknowledges that they cannot ignore AI any longer. While companies prepare their infrastructure to become equipped for AI, HR software providers are recommended to develop their software and leverage success stories. The head of Research and Development would be recommended to engage, in the short-term, in the development of predictive hiring analytics tools. The topical debate on diversity and inclusion and the current tight labour market makes calls for increased objective and predictive decision-making. According to this study, this can be achieved by supportive AI tools predicting candidates' success probability by evaluating them against high-performer benchmarking criteria. The prevention of turnover costs in this currently highly intensive HR practice marks an interesting business case for HR departments, especially at large corporates. Furthermore, HR software providers are advised to match their supply to the demands of the new generation of employees who would like to be empowered. HR wants to set this in motion by means of AI-enabled self-service tools. With life-long learning through all layers of the workforce being the new normal, it is recommended to designate developments of AI-steered self-service tools to the training- and development practice. Finally, the marketing and sales- and development teams at HR software providers are recommended to embrace AI's predictive power, as this is considered the future gem in HR. In the short-term it is specifically important to be able to provide companies with predictions on successful candidate matches. Moreover, it is crucial to predict absenteeism-, burn-out-, or turnover risk such that HR can proactively sustain employee well-being. To become a future market leader, HR software providers are advised to conduct research on, and invest in software solutions that can predict the future of HR-related topics (i.e., unemployment in industries). This would align to HR's ultimate goal: predicting uninfluenceable external forces.

For decision-making units involved in choosing a new AI-enabled HR software solution, the following is advised. Together with the HR software company, critically discuss how to create transparency to the workforce on the integration of AI into HR. Critically evaluate whether you have the knowledge for this in your company or whether it is too complex to grasp. This is important for determining a strategy to safeguard the validation of AI outcomes. Discuss with the HR software company what role they could play in monitoring the accuracy and reliability of AI. Bear in mind that any uncertainty and doubts about the deployment of AI technology could not only cause mistrust in AI but also mistrust in HR. Finally, it is recommended to stick to clear boundaries regarding the deployment of AI technology, whereby it is advised to only pursue AI automation in administrative tasks. Thereby it is recommended that these boundaries are also openly communicated to the workforce. It is recommended to assure, prior to adoption, that transparency can be provided on the parameters on which AI's support to HR's decision-making is based.

7. | CONCLUSION

This literary work attempted to explain why specialists- and managers in HR parts of technology would either capitalize the power of AI for HR purposes or would rather remain disengaged in AI-enabled HR practices. By placing the HR attributional theory in an AI context, this study has revealed that people attribute different emotions to AI-enabled HR practices than they do to generic HR practices. Favouring AI integration in the HR discipline stems predominantly from the human impotency in transferring career ownership to employees and from the lack of resources to constitute the proactive-, preventive-, and data-driven approach the HR discipline calls for. The necessity to reinvent HR practices based on AI is amongst others shaped by contextual influences such as the Covid-19 pandemic, topical debate on inclusion and diversity and tight labour market. AI is specifically perceived as valuable in the HR practice of recruitment and selection as the experience-based conviction prevails that AI ought to increase workforce inclusion and diversity and diminishes (early) employee turnover. Furthermore, with lifelong learning as the new normal, AI also appears to be desired in the HR practice of training- and development. AI is perceived as a facilitator to constitute personalized training opportunities and employee empowerment. AI adoption however also comes with concerns about employee distrust and commercial data exploitation. Whether these concerns turn into rejective tendencies depends on the perception of the complexity of AI and on the personality of the decision-maker. The intent to remain disengaged in AI-enabled HR practices prevails when AI automation is pursued in final decision-making on who to hire, fire, or promote for instance. The concerns on datafication, exclusion, diminished human sense-making, and objectifiable outcomes leverage worries about HR being able to become the advocate of employees. It therefore could be said that as long as AI is adopted with the intent to automate administrative tasks and to support strategic decision-making, AI is perceived as a diamond in the rough for HR.

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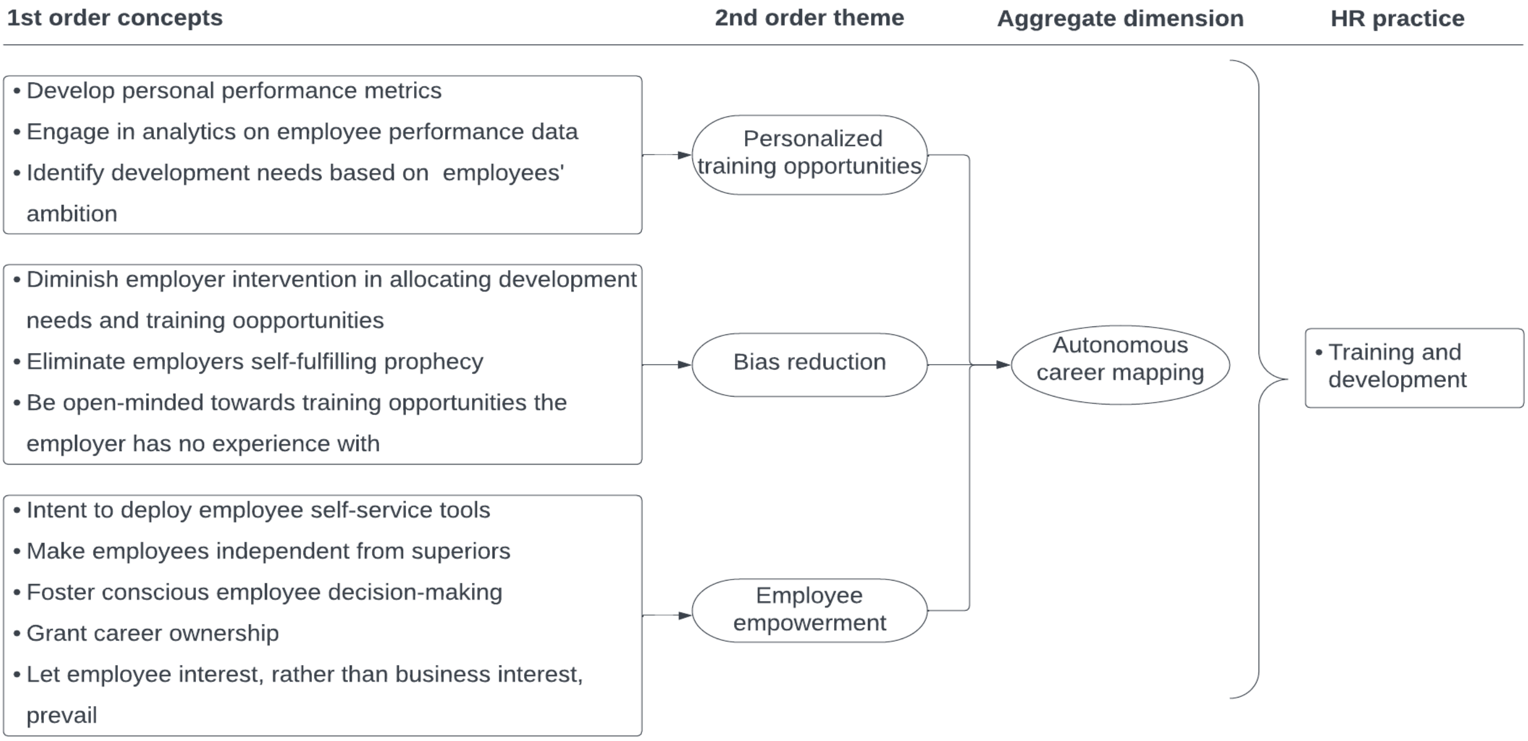
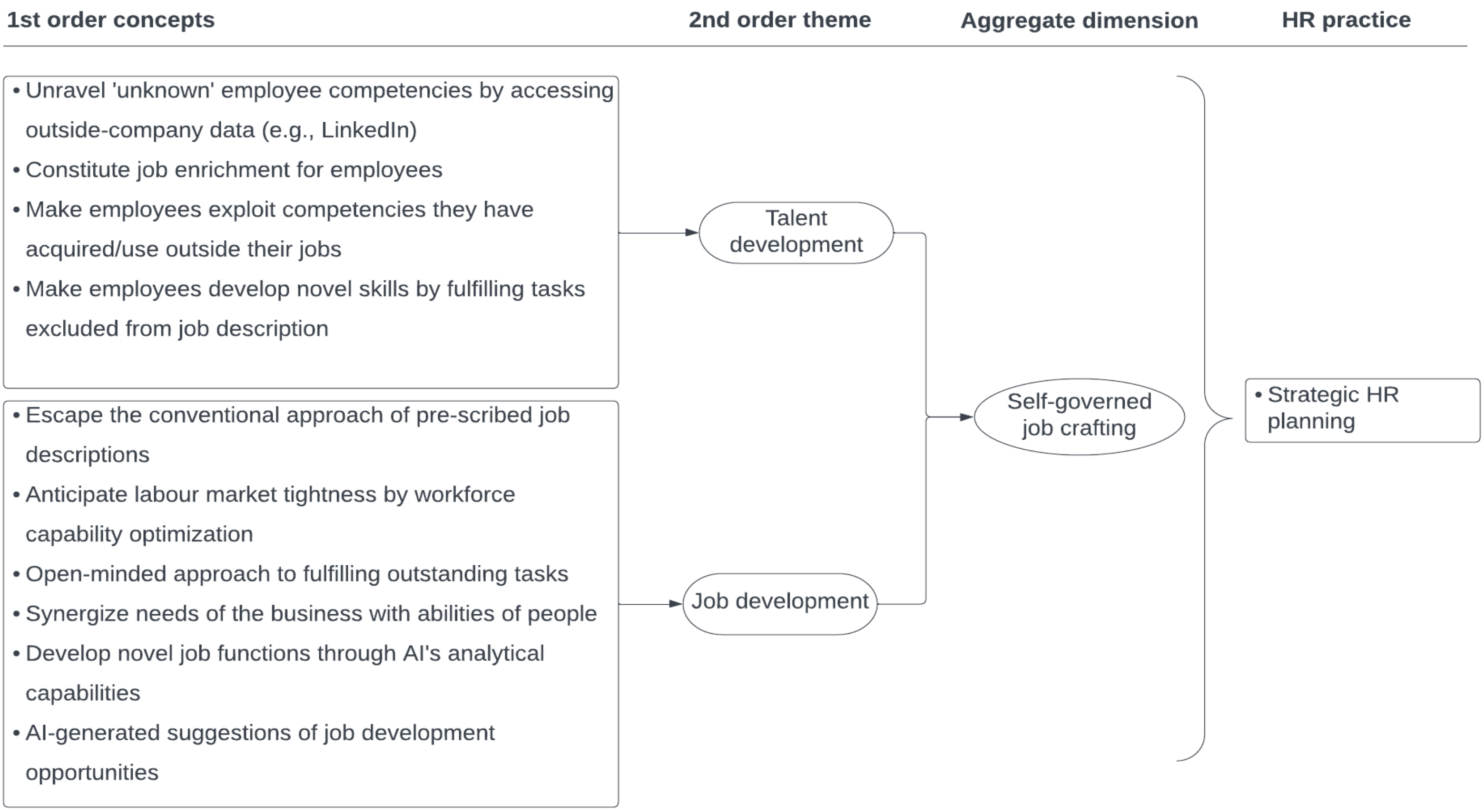
APPENDIX I: Coding Schemes

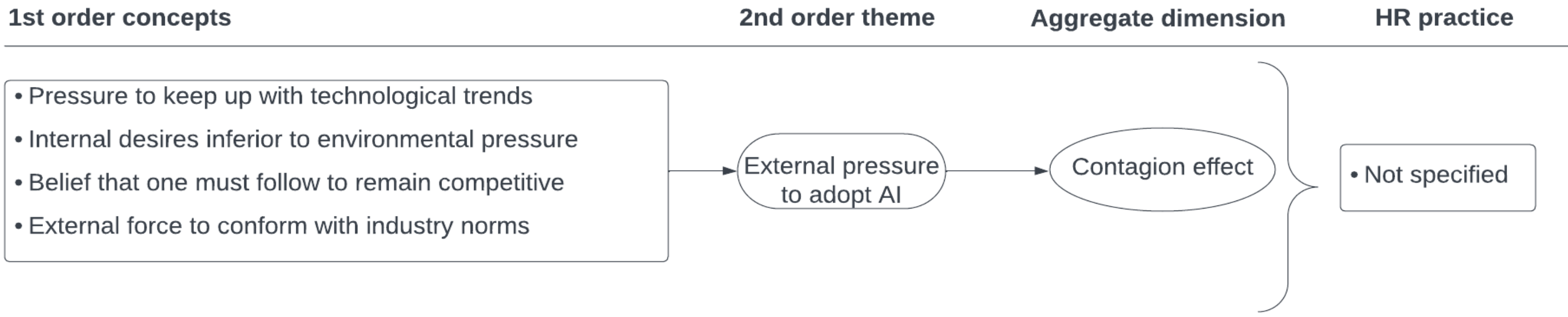
Coding scheme autonomous career mapping



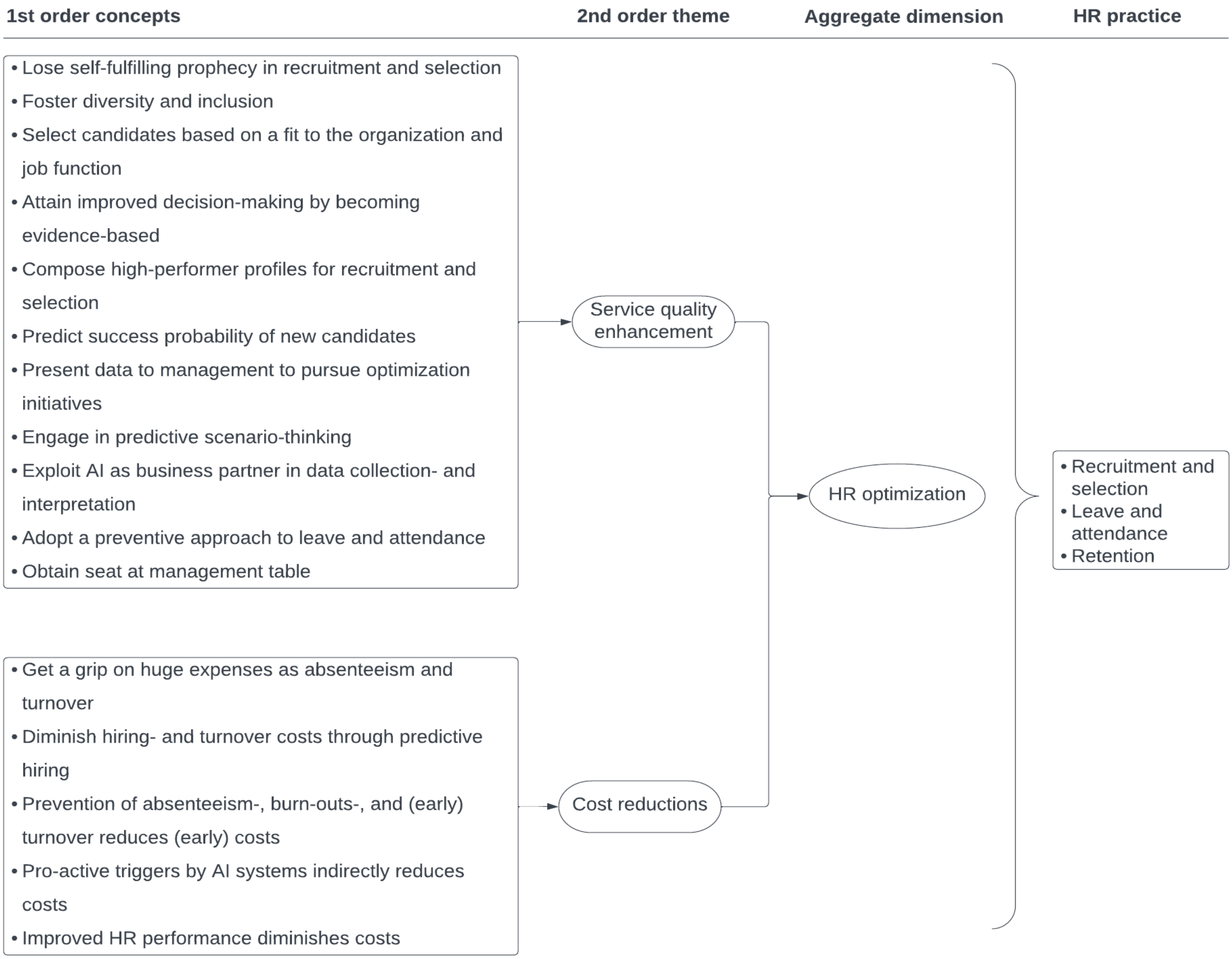
Coding scheme self-governed job crafting



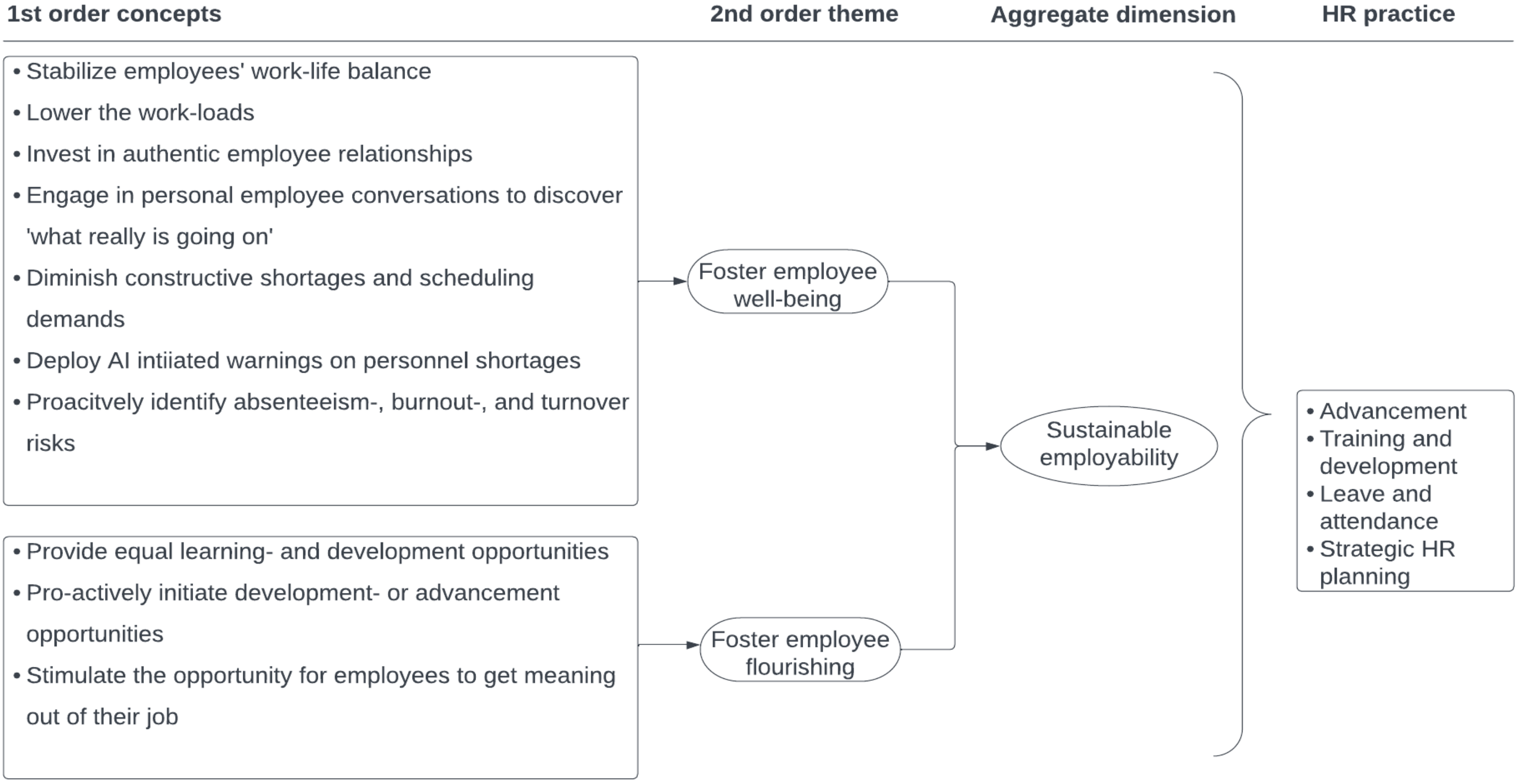
Coding scheme contagion effect



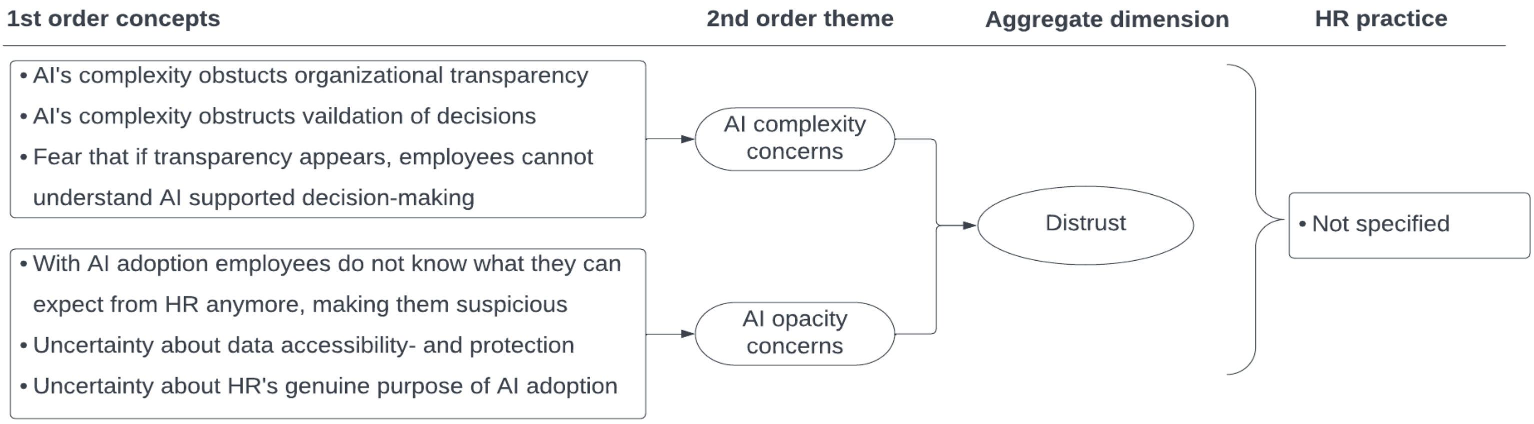
Coding scheme HR optimization



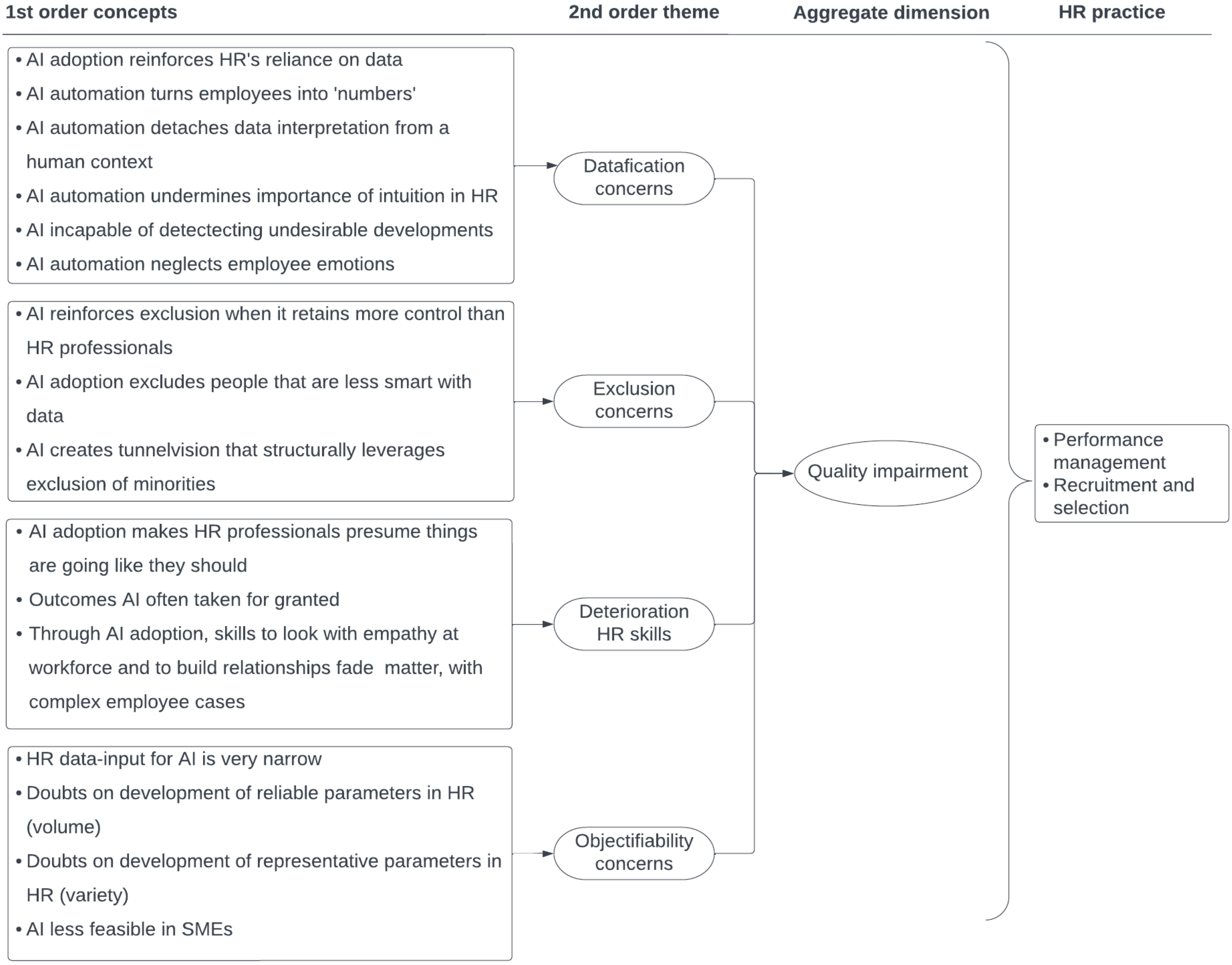
Coding scheme sustainable employability



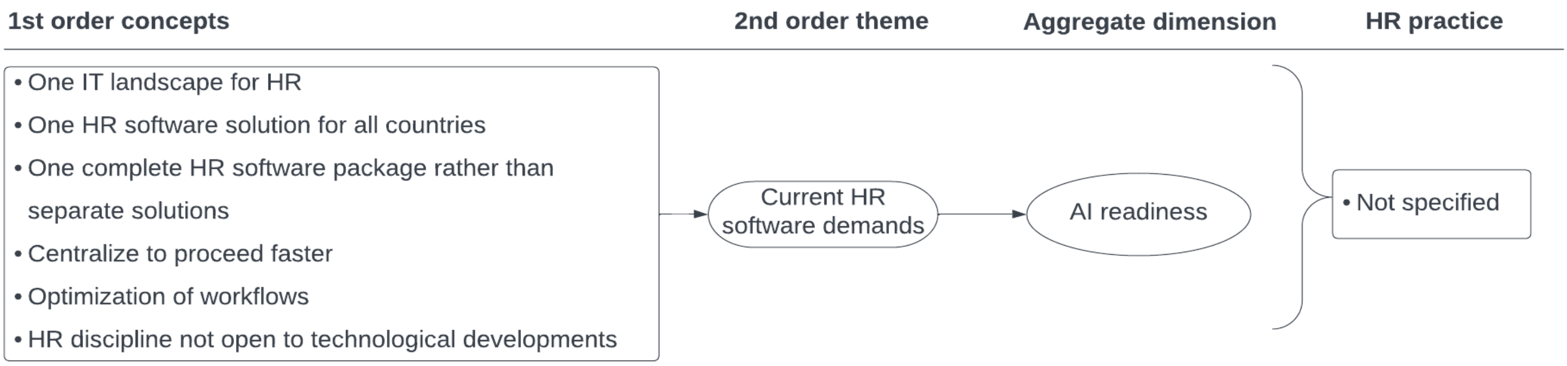
Coding scheme distrust



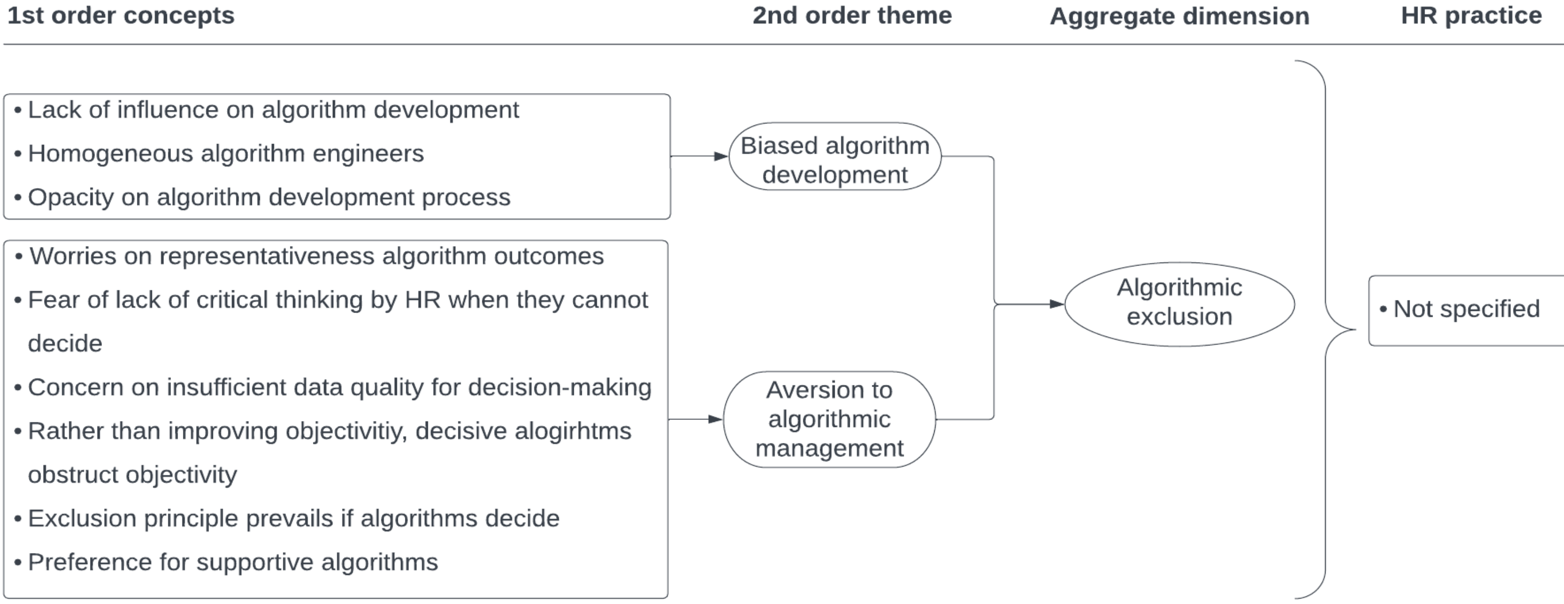
Coding scheme quality impairment



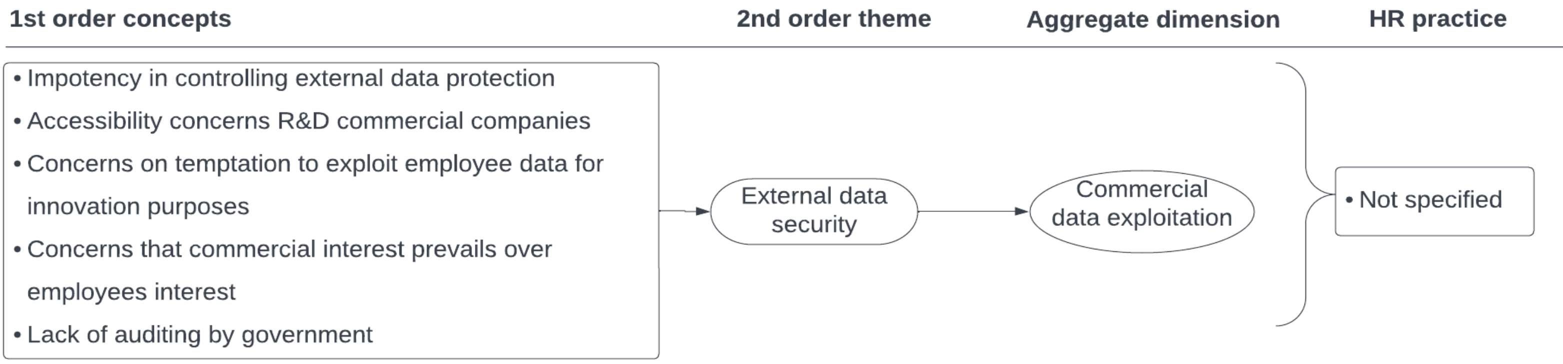
Coding scheme AI readiness



Coding scheme algorithmic exclusion



Coding scheme commercial data exploitation



APPENDIX II: Classifications of Attribution Typologies

The table in this appendix provides an explanation on the classification categories the typologies of the attributions towards the adoption and rejection of AI-enabled HR practices consist of.

Classifications	Definition
Internal attribution	The internal attributions stipulate intrinsic objectives that explain why organizations are eager to adopt- or reject AI-enabled HR software solutions. The desire or averseness towards AI-enabled HR practices reflects convictions that are organizationally focused rather than environmentally focused (i.e., competition oriented).
External attribution	The external attributions signify organizations as a passive recipient of environmental forces in which external pressure and constraints are fundamental to the willingness of adopting- or rejecting AI-enabled HR practices.
Strategic employee centric approach	The strategic employee centric approach reflects attributions in which the approach towards AI-enabled HR practices is profoundly influenced by the intention to reach a specific employee-oriented outcome. The adoption or rejection of AI is made in the interest of the employee and therefore outweighs any business-oriented benefits or drawbacks. The term strategic indicates that the employee-centric approach simultaneously could facilitate business-centric outcomes.
Strategic business centric approach	A strategic business centric approach reflects attributions in which the approach for AI-enabled HR practices is profoundly influenced by the intention to reach a business-oriented outcome. The adoption or rejection of AI is made in the interest of the company and therefore outweighs any employee-oriented benefits or drawbacks. The term strategic indicates that the business-centric approach simultaneously could facilitate employee-centric outcomes.
Employee ownership	Employee ownership refers to attributions in which the willingness to adopt AI stems from the intent to make employees in control of- and responsible for utilizing the AI-system to generate either the employee-centric or business-centric outcomes.
Organizational ownership	Organizational ownership refers to attributions in which the willingness to adopt AI system from the intent to maintain organizations in control of and responsible for utilizing the AI-system to generate either the employee-centric or business centric outcomes.

APPENDIX III: Positioning of Attributions Towards Adoption of AI-enabled HR practices

The table in this appendix provides a clarification on the positioning of the attributions concerning the adoption of AI-enabled HR practices.

Attribution	Internal vs External	Strategic approach	Ownership
Autonomous career mapping	**Internal:** intrinsic motivation to exploit AI's analytical capabilities and contribution to objectivity to provide employees with personalized training recommendations.	**Employee centric:** AI adopted with the intent to provide employee learning ownership rather than seeking a strategic match to an open function that requires staffing, but which is not inherent to that person's personality and ambitions.	**Employee ownership:** employee ought to be responsible for collaborating with the AI system to identify suitable training opportunities for his or her own development.
Self-governed job crafting	**Internal:** the intent is to optimize workforce capabilities to 'make the picture complete' and do more with less. This is not set in motion as a response to competitors.	**Business centric:** the aim to introduce AI is to optimally deploy, by means of job development, the workforce capabilities that matches the internal job demands. The potential advantages in terms of job enrichment (employee-oriented) are considered as an outcome of the adoption.	**Employee ownership:** Employees possess ownership while it is their conscious and deliberate choice to align their LinkedIn profile to their already available employee data to set in motion the job- and talent development.
Sustainable employability	**Internal:** the intent is to, by means of AI, be able to better comply with the renewed priorities in light of employee well-being and employee-flourishing.	**Employee centric:** The employee orientation in terms well-being and flourishing reflects the guiding principle towards the AI adoption in HR. The long-term relationships that are subsequently established seem to be a beneficial side-effect, as it might simultaneously foster retention.	**Organizational ownership:** the intent is that AI becomes supportive to the organizational responsibility in shaping HR activities to serve employee-oriented health- and satisfaction purposes.

HR optimization	**Internal**: an internal desire to enhance the performance of HR practices performed, as well as diminishing costs, prevails. AI is not adopted as a response to external constraints.	**Business centric:** intent for AI adoption specifically business oriented as improved performance of the HR practices is explicitly related to realizing cost reductions.	**Organizational ownership:** organizations are accounted to be mostly responsible for enhancing performance of the HR practices and realizing cost-reductions by means of AI-enabled HR practices.
Contagion effect	**External:** Organizations experience indirect pressure in keeping up with technological advancements that already appear to be prevailing in, HR departments of, other businesses. If this precedes the intent to make HR practices AI-enabled, the willingness is conformity-based.	Not applicable	Not applicable

APPENDIX IV: Positioning of Attributions Towards Rejection of AI-enabled HR practices

The table in this appendix provides a clarification on the positioning of the attributions concerning the rejection of AI-enabled HR practices.

Attribution	Internal vs External	Centric
Distrust	**Internal:** organizations are considered, regardless of the complexity of AI, to be in control of- and responsible for the transparency they offer about AI-enabled HR practices.	**Employee centric:** It is explicitly addressed that HR wants employees to be able to trust that everything is correct. A rejection of AI-enabled HR practices would stem from the lack of compliance to this motive, rather than to any strategic business motives.
Quality impairment	**Internal:** organizations themselves have the power to determine how they would like to deploy the AI technology to prevent internal issues with regard to exclusion and datafication that impairs the quality of HR practices performed.	**Business centric:** the rejection of AI-enabled HR practices is bound to the fear of quality impairment of HR practices for which the business ought to be responsible. AI rejection would primarily be a strategic business motive to safeguard HR's quality.
AI readiness	**Internal:** organizations possess control over their openness towards AI-enabled change and they are themselves responsible to prepare their HR department for AI adoption.	**Business centric:** Despite their desire to implement AI, the business is not ready for this. Just like the lack of AI readiness, the intent towards rejection is not related to employees.
Algorithmic exclusion	**External:** organizations cannot exert influence on the development of algorithms that are included in the AI-enabled HR software solutions offered by software providers. This means that they, due to external constraints, do not want to engage in AI automation.	Not applicable

Commercial data exploitation	**External:** organizations cannot control whether and how commercial HR software providers secure employee data. Rejection could stem from the fear attributed to this data being exploited for innovation purposes.	Not applicable