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Organisational, Human, and Technological Perspectives on the Adoption of Data-Driven Human Resources Decision-Making

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Svenja Marie Pröpper (geb. Hülter), M.Sc.

ORCID: 0009-0001-3972-5135

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Erstgutachter:	Prof. Dr. Andreas Hoffjan
Zweitgutachter:	Prof. Dr. Jens Rowold
Mitglied der Prüfungskommission:	Prof. Dr. Andreas Liening

Vorwort

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Summary in German

Die digitale Transformation führt zu einer zunehmenden Nutzung von Daten für die Entscheidungsfindung im Personalmanagement (HRM); gleichzeitig gibt es jedoch noch wenige empirische Studien in diesem Bereich, insbesondere aus praktischen Anwendungsszenarien. Diese Dissertation untersucht die Einführung datengestützter Personalentscheidungen auf der Grundlage von drei empirischen Studien, die unterschiedliche organisatorische Kontexte und Stufen der Analytics-Reife aufweisen. Die erste und zweite Studie untersuchen die Einführung prädiktiver Analytics zur Vorhersage der freiwilligen Mitarbeiterfluktuation in einer deutschen Bundesbehörde. Die dritte Studie befasst sich mit temporären Managern, die von Organisationen in Krisensituationen eingestellt werden und Personalentscheidungen treffen. Die in dieser Studie befragten Manager verwenden in erster Linie deskriptive Analytics für ihre Entscheidungsfindung.

Die Ergebnisse der drei Studien legen nahe, dass technologische, organisatorische und menschliche Faktoren für die erfolgreiche Einführung datengestützter Personalentscheidungen von zentraler Bedeutung sind. Außerdem zeigen die Ergebnisse dieser Dissertation, dass die Einführung datengestützter Personalpraktiken ein komplexer, interdisziplinärer Prozess ist, der einen ganzheitlichen Ansatz erfordert. Technische Gegebenheiten allein reichen nicht aus, um datengestützte Personalentscheidungsprozesse angemessen einzuführen. Eine effektive Implementierung scheint auch von unterstützenden Organisationsstrukturen und -kulturen sowie von menschlichen Überzeugungen und Denkweisen abzuhängen. Fünf Bereiche ergeben sich für Empfehlungen zu praktischen Maßnahmen zur Unterstützung von Organisationen im Adoptionsprozess: Förderung einer datengesteuerten Kultur, Entwicklung einer Digitalisierungsstrategie, Bereitstellung von Fachwissen, Bereitstellung einer geeigneten IT-Infrastruktur und die Einrichtung eines Governance-Systems.

Letztendlich zeigt diese Dissertation, dass es keine Einheitslösungen für die Einführung datengestützter Personalentscheidungen gibt. Stattdessen sind kontextspezifische Strategien erforderlich, die die technologischen, organisatorischen und menschlichen Dimensionen dynamisch und adaptiv aufeinander abstimmen – und so einen langfristigen Mehrwert für Unternehmen und Mitarbeitende sicherstellen.

Summary

The digital transformation is leading to an increasing use of data for decision-making in Human Resource Management (HRM); but at the same time, there are still few empirical studies in this area, particularly from practical application scenarios. This dissertation explores the adoption of data-driven Human Resource (HR) decision-making based on three empirical studies that feature different organisational contexts and stages of analytics maturity. The first and second studies examine the adoption of predictive analytics in a German federal agency to predict voluntary employee turnover. The third study considers the perspectives of temporary managers hired by organisations in crises and taking HR decisions. The temporary managers interviewed in this study primarily use descriptive analytics.

The results of the three studies suggest that technological, organisational, and human perspectives are central to the successful adoption of data-driven HR decision-making. Furthermore, the findings of this dissertation demonstrate that adopting data-driven HR practices is a complex, interdisciplinary process that necessitates a holistic approach. Technological foundations alone are not enough to adequately adopt data-driven HR decision-making. Effective adoption also seems to depend on supportive organisational structures and culture as well as on the salient beliefs and thinking patterns of individuals. Five areas emerge for recommendations for practical measures to support organisations in the adoption process: fostering a data-driven culture, developing a digital strategy, providing expertise, providing appropriate Information Technology (IT) infrastructure, and establishing a governance system.

Ultimately, this dissertation highlights that there are no one-size-fits-all solutions for adopting data-driven HR decision-making. Instead, it requires context-specific strategies that dynamically and adaptively align technological, organisational, and human dimensions – thereby ensuring long-term value for organisations and employees.

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List of Abbreviations

AI	Artificial Intelligence
ALE	Accumulated Local Effects
CEO	Chief Executive Officer
CRO	Chief Restructuring Officer
ERP	Enterprise Resource Planning
GDPR	General Data Protection Regulation
HR	Human Resources
HRA	Human Resource Analytics
HRIS	HR Information Systems
HRM	Human Resources Management
IT	Information Technology
κ	Cohen's Kappa
KPI	Key Performance Indicator
LIME	Local Agnostic Model Explanations
ML	Machine Learning
PBC	Perceived Behavioural Control
Q&A	Questions and Answers
ROC	Receiver Operating Characteristic
RQ	Research Question
SHAP	SHapley Additive exPlanations
SMEs	Small and Medium-Sized Enterprises
TPB	Theory of Planned Behaviour
XAI	Explainable Artificial Intelligence

1 Introduction

1.1 Motivation

> “***Information is the oil of the 21st century, and analytics is the combustion engine*.”** – Peter Sondergaard (2011)

Data assists in substantiating evaluations, optimising processes, and identifying patterns to make decisions that go beyond pure intuition. Wisdom in the information age lies not only in knowledge, but also in understanding the patterns that shape our world.

In recent decades, digital transformation has enabled the use of large volumes of data for organisational decision-making and operational processes. The terms *Big Data* and *Artificial Intelligence* (AI) are being used more frequently in this context. De Mauro et al. (2016) describe big data as the “*information asset characterised by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value*”. AI offers innovative technologies and methods, such as *Machine Learning* (ML), which possess cognitive abilities and learning functions that exhibit human-like intelligence (Pan et al. 2022). These capabilities enable them to achieve specific objectives and tasks (Haenlein and Kaplan 2019). AI has recently become the most significant source of process transformation, disruption, business model innovation, and competitive advantage for organisations that cultivate a data-centric and digital culture (Ransbotham et al. 2020).

The use of data has become indispensable in numerous business areas across various industries. It has contributed to the automation of entire core processes. For example, e-commerce giant Amazon uses big data to optimise its supply chain to manage stock levels and minimise delivery times efficiently. With the help of AI-supported algorithms, Amazon analyses customer behaviour and offers personalised product recommendations (Amazon 2025). The German industrial group Bosch builds smart factories in which sensors collect machine data and analyse it for efficient production control, while predictive maintenance reduces downtimes and maintenance costs (Bosch 2025). Additionally, new business models, such as the mobility platform Uber, have only emerged through the availability and use of a considerable amount of data. Uber is based on real-time data analysis to arrange rides between drivers and passengers while algorithms dynamically optimise prices and calculate the most efficient driving routes (Uber 2018).

The study by Brynjolfsson et al. (2011) demonstrates that the output and productivity companies experience through the adoption of data-driven decision-making is 5–6% higher than would be expected given other investments and the use of Information Technology (IT). There is a consensus in the literature about the enormous potential of algorithms that are increasingly able to perform tasks in a reliable way and could possibly even surpass humans in an increasing number of tasks (Faraj et al. 2018; Strich et al. 2021).

Although employees are often considered an organisation’s most important asset (Pfeffer and Veiga 1999), data-driven decision-making has not yet been widely applied in this area. In Human Resources Management (HRM) where decisions are taken that have a direct impact on humans and their careers in the form of salary changes, promotions or training, the use of big data lags behind other organisational areas (Angrave et al. 2016; Kryscynski et al. 2018; Vargas et al. 2018; Fernandez and Gallardo-Gallardo 2021), like finance or marketing (Rasmussen and Ulrich 2015). This may also be due to the fact that HRM is traditionally one of the least data-driven of all the organisational functions (Davenport 2014).

In addition to higher requirements for data protection compliance and data accuracy (Rasmussen and Ulrich 2015), the utilisation of data also offers great potential for HRM. Several empirical studies indicate significant advantages to using data-driven HR decision-making. The study by Aral et al. (2012) was one of the first to provide evidence that the adoption of fine-grained data use in human capital management is associated with a large productivity premium. Companies that introduce human capital management systems see greater benefits from the incentive system, primarily through their effects on talent selection and retention (Aral et al. 2012). Additionally, evidence is provided by Coco et al. (2011) who demonstrate through their case study how Lowe’s, an American home improvement retail chain, utilised analytics on Human Resource (HR) data to establish a connection between HRM processes, employee engagement, and store performance. Rasmussen and Ulrich (2015) report a similar case, where the positive assessment of managers is associated with lower employee turnover, higher workforce competence, and thus higher performance. Furthermore, Daugherty et al. (2018) propose potential ways to utilise AI tools to promote diversity. Tursunbayeva et al. (2022) demonstrate that HR Analytics enables organisations to identify the most effective training programs and make informed budget allocation decisions, thereby improving employee skills and organisational performance. According to Theres and Strohmeier (2024), AI algorithms can improve the efficiency and effectiveness of HR practices by analysing both historical and real-time data to identify patterns and generate actionable recommendations.

In addition to the advantages from the organisational perspective, Margherita (2022) summarises the benefits from the employee's perspective in his review. They range from higher employee engagement and commitment, improved employee experience, targeted leadership development, and a better skill-job fit, to customised training, fair pay, greater loyalty, and wage transparency. The integration of data-driven methods into HR decision-making promises greater objectivity and transparency (Shah et al. 2017; Theres and Strohmeier 2024), thus comprehensive advantages for employees. From a methodological perspective, Rombaut and Guerry (2018) further emphasise that the use of existing data in HRM decision-making offers the opportunity to go beyond traditional approaches such as survey data.

Other studies shed a sceptical light on the potential consequences of data-driven HR decision-making and highlight the potential downsides (e.g. Minbaeva 2021; Speer 2021; Dastin 2022; Alon-Barkat and Busuioc 2023). Minbaeva (2021) argues that the use of advanced algorithms can improve systems or cause harm depending on how they are used. She backs up this proposition with the example of IBM's flawed performance algorithm which favoured newer employees, leading to biased outcomes and the loss of around 20,000 experienced workers. This illustrates the far-reaching risks of poorly designed algorithms in HRM. The experimental study by Alon-Barkat and Busuioc (2023) comes to similar conclusions. Their study shows that while AI in public decision-making aims to reduce bias, it can also create new bias. It also emphasises that people often follow algorithmic advice when it aligns with stereotypes, while the Dutch childcare benefits scandal demonstrates how such biases can harm vulnerable and disadvantaged groups (Alon-Barkat and Busuioc 2023).

The publications in diverse scientific outlets such as *HRM*, *Information Systems* and *Management* reflect the interdisciplinary nature and wide spectrum of research directions within the field of data-driven HR decision-making (e.g. see Marler and Boudreau 2017; Margherita 2022; McCartney and Fu 2022b). The adoption and use of data-driven HR decision-making is examined from different angles such as the potential value propositions (e.g. Aral et al. 2012; Rasmussen and Ulrich 2015; Tursunbayeva et al. 2018), ethics (e.g. Simbeck 2019; Gal et al. 2020; Speer 2021; Tursunbayeva et al. 2022; Edwards et al. 2022; Hunkenschroer and Luetge 2022), and technical realisation (e.g. Strohmeier and Piazza 2015; Rombaut and Guerry 2018; Chowdhury et al. 2023b).

In recent years, a variety of terms and definitions have emerged in different contexts. The labels *HR Analytics*, *People Analytics*, *Workforce Analytics*, *Talent Analytics* (e.g. Tursunbayeva et al. 2018; Margherita 2022; Giermindl et al. 2022; Fernandez and Gallardo-Gallardo 2021), or, more recently, *AI in HRM* and *Algorithmic HRM* (e.g. Meijerink et al. 2021; Duggan et al. 2023; Chowdhury et al. 2023a), are frequently used in the literature.

One of the first definitions goes back to Davenport and Harris (2007), who describe HR Analytics as a “*data-based approach to people management, using statistical and quantitative analyses and explanatory and predictive models*”. Marler and Boudreau (2017) provide a more detailed and widely used definition. They describe HR Analytics as “*an HR practice enabled by information technology that uses descriptive, visual and statistical analyses of data related to HR processes, human capital, organisational performance and external economic benchmarks to establish business impact and to enable data-driven decision-making*”. In contrast, Meijerink et al. (2021) encompass a wider field with their definition which includes platform work. That is a form of work that is only enabled by AI: “*Algorithmic HRM is the use of software algorithms that operate on the basis of digital data to augment HR-related decisions or to automate HRM activities*”. Fernandez and Gallardo-Gallardo (2021) sum up that data-driven HR decision-making “*aim[s] to provide reliable foundations for people-related decisions (i.e. data-driven decisions) that affect the individual and organisational outcomes*”.

One common feature of all these terms and definitions is that they do not refer to a specific technology (Gal et al. 2020). Although the terms have different priorities, they ultimately refer to comparable fundamental concepts, namely the use of data and technologies for HR decision-making. Due to these fundamental similarities, the terms are used synonymously in this thesis as they are essentially based on the same methods, approaches, practices and basic ideas. The focus of this dissertation is on decision-making support with the aid of data; the ultimate decision-making power remains with the individual. Completely automated decisions by technologies are therefore outside the scope of this thesis.

The next section provides an overview of the basic principles of data-driven HR decision-making including technologies applied, application areas, and data used. This creates a consistent understanding of the underlying concepts, especially for the subsequent discussion of the results.

1.2 Technologies for Data-Driven Decision-Making in HR Practices

Technology, particularly data analytics methods, has developed rapidly and become the central enabler of data-driven decision-making processes in recent decades (Oswald et al. 2020). In this sense, the technologies are often called *Analytics*, which is also the focus of this dissertation, as this field plays a central role in generating data-based insights and thus has a direct influence on organisational decision-making and strategy processes. Analytics enables the processing, interpretation, and visualisation of large amounts of data. Thus, it provides significant added value in today's data-driven economy (Davenport and Harris 2007; Guenole et al. 2015; Marler and Boudreau 2017; Shamim et al. 2019).

In academic literature, analytics is generally categorised into three stages of maturity (Davenport 2013; Delen and Demirkan 2013; King 2016). The first stage of maturity involves building *Descriptive Analytics*, which systematically evaluates past data with the help of reporting, scorecards, or dashboards (Davenport 2013; Delen and Demirkan 2013; Margherita 2022). While *Predictive Analytics* uses technologies such as advanced regression techniques, ML algorithms, or Data Mining to predict future developments, *Prescriptive Analytics* derives specific alternative courses of action using decision modelling, simulations, or scenario-based techniques (Davenport 2013; Delen and Demirkan 2013; Giermindl et al. 2022; Margherita 2022). ML is becoming increasingly popular. Samuel (1959) defines it commonly as "*the ability of algorithms to learn without being explicitly programmed*". Figure 1 summarises the three maturity stages of analytics.

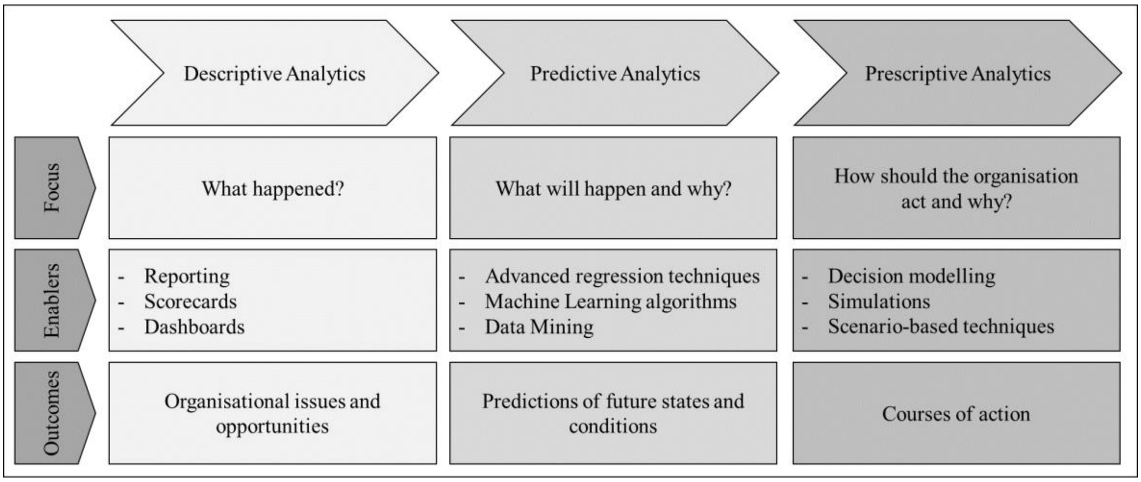

Figure 1: Maturity stages of analytics (based on: Delen and Demirkan 2013)

This dissertation uses the term *Advanced Analytics* to refer specifically to the maturity stages of predictive and prescriptive analytics.

The term *AI* is used in literature and practice as a generic term for various technologies that show human-like intelligence such as ML, Robotic Process Automation or computer vision techniques (Budhwar et al. 2023). It is also frequently discussed in the context of HRM. To ensure a comprehensive and consistent understanding of AI in the HRM context, Chowdhury et al. (2023a) review definitions from multiple disciplines and define AI "*as the ability of a manmade system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from data sources to achieve specific predetermined goals and tasks*". In this context, generative AI is one of the latest developments with significant potential to transform today's workplace and HRM. Initial studies evaluate the benefits and risks of generative AI tools such as ChatGPT in the field of HRM and investigate the extent to which these tools can be helpful for strategic and operational HR tasks (e.g. Budhwar et al. 2023; Aguinis et al. 2024). Aguinis et al. (2024) conclude by describing ChatGPT and its potential as "*a multi-tool pocketknife [for HRM professionals], offering a versatile, efficient, and adaptable tool that can be essential across HRM areas*".

The HR practices of an organisation can encompass a range of distinct roles and activities depending on internal organisational processes, labour market challenges, legal requirements, and other factors. In the context of data-driven decisions, five key HR practices emerge in the literature: recruitment and selection, training and development, performance assessment, compensation and benefits, and workforce planning and attrition (Tursunbayeva et al. 2018; Meijerink and Bondarouk 2023; Ramachandran et al. 2023; Thakral et al. 2023). Figure 2 summarises these five key HR practices.

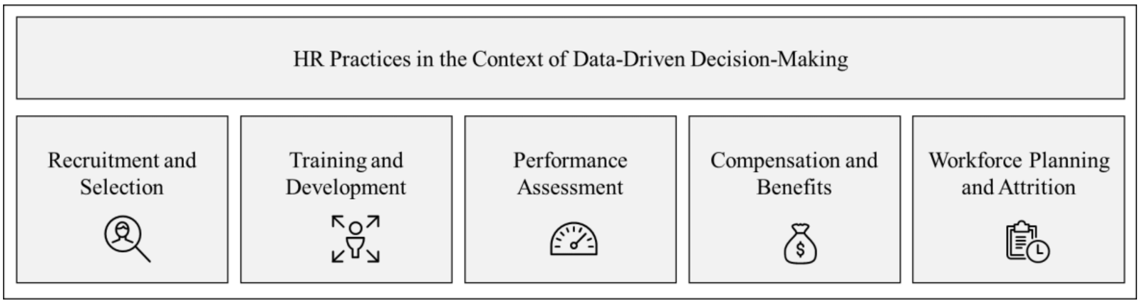

Figure 2: HR practices in the context of data-driven decision-making

Meijerink and Bondarouk (2023) provide a literature-based overview illustrating current and potential applications of descriptive, predictive, and prescriptive analytics with HR data. The various applications in the three maturity stages presented in Table 1 clearly underline the potential opportunities for the development of data-driven decision-making processes across different facets of HRM. The potential for efficiency gains, process acceleration, and optimised planning bases is becoming apparent in various HR practices.

However, ethical issues related to automated decision-making processes should be thoroughly examined and addressed. Further, Ulrich and Dulebohn (2015) underline that decisions can be initiated at various levels including individual, organisational, and management levels.

Table 1: Overview of data-driven HR practices (taken from: Meijerink and Bondarouk 2023)

	HRM algorithm type		
	Descriptive Analytics	**Predictive Analytics**	**Prescriptive Analytics**
Recruitment and Selection	Assessment of job candidates' personality traits on basis of their social media profiles	Predicting job candidates' potential and performance	Automated resume screening; automated suggestions which job candidate to invite for job interview
Training and Development	Automated web-search of available training programmes; evaluation of training effectiveness	Predicting the need for upskilling; prediction of workforce competence gaps	Automated instructions to poor performing workers
Performance Assessment	Sentiment analysis; aggregation and computing performance scores	Predicting when projects go off track; predicting future worker performance	Alerting managers to take corrective actions; automated sanctioning of poor performing workers
Compensation and Benefits	Automated salary surveying; job ranking	Predicting desired compensation level	Surge pricing; automated variable pay; priority access to work assignments
Workforce Planning and Attrition	Construction of competency profiles; employee inventory	Turnover prediction; predicting future labour demand	Automated staff rostering; automated task allocation

In addition to the technological capabilities themselves, data is a crucial resource for data-driven HR decision-making. There is consensus in the literature that both internal and external data should be utilised (Rasmussen and Ulrich 2015; Marler and Boudreau 2017). Fernandez and Gallardo-Gallardo (2021) summarise that the data collected at the individual employee level may relate to:

(1) The individual employee (e.g. skills),

(2) the employee outside the organisation (e.g. education),

(3) the position of the employee in the organisation (e.g. salary) and

(4) the work carried out in the organisation (e.g. performance evaluations).

The storage and processing of this data pose challenges for the organisations because sensitive personal data is involved. As Marler and Boudreau (2017) and Harris et al. (2011) emphasise, ensuring data privacy and data security is vital to protect employees and to maintain trust within the organisations. Under the European Union's General Data Protection Regulation (GDPR), the core European framework for data protection law, non-compliance can result in severe penalties including fines up to 20 million euros or 4% of the annual global turnover, highlighting the legal and ethical importance of responsible data handling in HRM (GDPR 2016; Tursunbayeva et al. 2022). The focus is increasingly on data fairness and transparency when it comes to HR data (Alam et al. 2025). McCartney and Fu (2022a) define data fairness as the practice of preventing bias related to personal attributes such as gender, age, or ethnicity in both data collection and data analysis. In addition, HR data is often unstructured, incomplete, fragmented, and dispersed across various departments (Marler and Boudreau 2017; Hamilton and Sodeman 2020; Shet et al. 2021), which can compromise data quality and the decision-making process based on it. Marler and Boudreau (2017), as well as Rasmussen and Ulrich (2015), highlight the need to use data from outside HR data sources such as data from other functional areas of the organisation (like finance and production) and from external data sources. These challenges underscore the need for robust data management and strict adherence to legal and ethical frameworks.

In this dissertation, adoption is conceptualised as a dynamic, ongoing, and evolving process instead of a single instance. This is argued based on the complex nature of the investigated innovative technologies and their non-linear realisation.

The next section provides an overview of the current body of research, underlines the research objective of this dissertation, and introduces the three studies included in this thesis.

1.3 Research Objective and Included Studies

Although the number of publications on data-driven HR decision-making has increased significantly in recent decades (Qamar and Samad 2022), there is sparse evidence from empirical research (Edwards et al. 2022), particularly in practical application scenarios. Giermindl et al. (2022) summarise that the current literature on data-driven HR decision-making focuses primarily on what it is, how it operates, its implementation prerequisites, and the emerging value proposition it offers. The current body of literature includes a significant share of reviews (Edwards et al. 2022, see e.g. Marler and Boudreau 2017;

Giermindl et al. 2022; Margherita 2022; Tursunbayeva et al. 2022; Coolen et al. 2023; Meijerink and Bondarouk 2023; Alam et al. 2025) and hypothetical application scenarios for ML or other technologies in HRM (Langer and Landers 2021, e.g. Strohmeier and Piazza 2015; Rombaut and Guerry 2018; Chowdhury et al. 2023b).

While studies predominantly paint an optimistic picture of how HR data could support organisational decision-making (Giermindl et al. 2022), Charlwood and Guenole (2022) suggest that there is little research that sheds light on concrete adoption scenarios for data-driven HR decisions in a practical setting (only the study by van den Broek et al. 2021). The different strands of research give various arguments for the introduction of data-driven HR decisions and the requirements that must be met in this context, which are often based solely on conclusions drawn from the literature (e.g. Margherita 2022; Böhmer and Schinnenburg 2023; Coolen et al. 2023). Bahuguna et al. (2023) share the view that more research is needed and specifically call for a more empirically oriented methodology. Diefenhardt et al. (2024) likewise call for more research on the implementation of data-driven HR decision-making. Furthermore, Pan et al. (2022) critically summarise that, from an HRM viewpoint, academic research lags behind the industry’s awareness of the significance of AI for the future of HRM.

With the three studies included in this thesis, this dissertation aims to provide empirical evidence on the adoption of various technologies into HR decision-making in different empirical environments. To obtain a more comprehensive picture, this thesis considers different contexts and technologies in the field of data-driven HR decision-making. Over the course of the investigation, it becomes evident that the adoption of data-driven decision-making in HRM is particularly influenced by technological, organisational, and human factors. These three key perspectives are also reflected in the current literature, which further encourages their use as a framework for structuring the comprehensive discussion of this dissertation. Through these investigations, this dissertation aims to empirically gain a broad understanding of the enablers and barriers that influence the adoption of data-driven HR decision-making.

Studies one and two emerged from the same empirical environment and dealt with the second maturity stage of analytics, namely the use of predictive analytics. The object of investigation for the two studies is a German federal agency with around 20,000 employees. Overall, the level of digitisation can be assessed as low to medium. In the specific subject of the study, several different (ML) algorithms were applied to predict voluntary employee turnover, which can be attributed to the key HR practice of workforce planning and attrition. The in-depth investigation, which includes (HR) data from internal Enterprise Resource Planning (ERP) systems, interviews, guidelines, and project meetings provides a broad picture of the internal processes and the organisational culture. The data basis for the (ML) algorithms comprises both internal and external data sources. Internal HR databases provide employee-related data, which is complemented by external data such as the unemployment rate in Germany and employee satisfaction metrics. The first study uses an empirical-inductive analytical research approach while the second study is based on an empirical-qualitative approach that relies on *Focused Interviews* with twelve employees of the federal agency. This research environment also supports the call by Wirtz et al. (2021) for more empirical studies on the adoption of AI projects in the public sector, especially on real-life cases of AI applications. In addition, the second study of this thesis continues to address the research gap regarding the adoption of AI in the public sector from the perspective of employees, particularly in Germany (Schaefer et al. 2021).

The third study looks at temporary executives, often referred to as interim managers, assigned in crisis-inflicted situations. In total, seventeen managers from nine different European countries were interviewed to gain a comprehensive understanding of the dynamics, the decision-making processes, and the various approaches employed by these temporary managers in HR decision-making. In the research environment, descriptive analytics is primarily used for HR decision-making. Analytical methods including reporting, dashboards, and tables are utilised to establish a data-driven foundation for informed decision-making in HRM. In addition, study participants use more advanced technologies such as generative AI to a certain extent, for example, to support and prepare decisions, but not to fully automate processes. The study covers a variety of organisations from different industries and European contexts. The organisations examined differ in terms of their structure, size, and HR strategy, meaning that a wide range of HR-related decision-making processes are considered. These vary according to the specific requirements and circumstances of the respective organisation that hires the temporary manager. In general, temporary managers report a lower overall level of digitisation in their respective organisations. The database the managers use consists mainly of internal organisational data. In some cases, they collect their own data to gain additional context-specific information. This enables temporary managers to conduct a detailed analysis of the respective challenges in HRM and supports the development of data-driven HR strategies. The characteristics of the empirical contexts of the studies are summarised briefly in Table 2.

Table 2: Overview of empirical contexts of included studies

	Study no.	
	1 and 2	**3**
Research Environment	German federal agency, employees with similar tasks (processing of special applications), low to medium level of digitalisation	Various companies in crisis situations, different European countries, different but mainly low levels of digitalisation
Applied Technology	Predictive Analytics (Machine Learning)	Preliminary Descriptive Analytics (reporting, dashboards etc.), partial use of AI (rather for decision preparation)
Focused HR Practices	Workforce planning and attrition (voluntary employee turnover prediction)	Wide range of decisions, depending on hiring organisations
Object of Investigation	One organisation (German federal agency)	Several organisations in crises (different sectors, European sample)
Data for Decision-Making	Data from internal (HR) and external databases	Mainly internal data (verbal information, data from internal (HR) databases)

From a research perspective, this dissertation aims to systematically structure, discuss, and synthesise the empirically identified technological, organisational, and human factors that influence the adoption of data-driven HR decision-making. By using a comprehensive framework and discussing the main findings of the three studies, the complex interrelations between these three dimensions also become apparent. As a result, the dissertation contributes to a more nuanced understanding of how the three dimensions of technology, organisation, and human factors jointly shape the adoption process in various organisational contexts.

From a practical perspective, this dissertation provides a detailed overview of the organisational considerations needed to adopt data-driven HR decision-making effectively. Among other things, this thesis aims to provide concrete measures and recommendations that organisations can follow as a roadmap to successfully introduce data-driven decision-making in HRM.

To conclude the introductory section, Tables 3, 4 and 5 summarise the publication details of the three included studies of this thesis.

Table 3: Publication details study one

Study no.	**1**	
Title	**Machine Learning with Real-World HR Data: Mitigating the Trade-Off between Predictive Performance and Transparency**	
Co-Authors	Ansgar Heidemann, Michael Tekieli	
Research Approach	Empirical-inductive, analytical	
Publication Status	Published	
Journal	International Journal of Human Resource Management	
Journal Metrics	Journal-Ranking (VHB-Rating 2024)[1]:	A
	Journal Impact Factor 2024[2]:	5.9 (Quartile 1)
	Journal CiteScore 2024[3]:	13.3 (Quartile 1)
	SCImago Journal Rank 2024[4]:	2.231 (Quartile 1)
Presentations	- 37th EIASM Workshop on Strategic Human Resource Management, Minho (Portugal) - 1st EIASM Workshop on People Analytics and Algorithmic Management (PAAM), Dublin (Ireland) - Research Seminar University of Twente 2022, Enschede (Netherlands) - Berens Doctoral Seminar 2022, Bayreuth (Germany) - Brown Bag TU Dortmund 2022, Dortmund (Germany)	
Summary	Machine Learning (ML) algorithms offer a powerful tool for capturing multifaceted relationships through inductive research to gain insights and support decision-making in practice. This study contributes to understanding the dilemma whereby the more complex ML becomes, the more its value proposition can be compromised by its opacity. Using a longitudinal dataset on voluntary employee turnover from a German federal agency, we provide evidence for the underlying trade-off between predictive performance and transparency for ML, which has not been found in similar Human Resource Management (HRM) studies using artificially simulated datasets. We then propose measures to mitigate this trade-off by demonstrating the use of post-hoc explanatory methods to extract local (employee-specific) and global (organisation-wide) predictor effects. After that, we discuss their limitations, providing a nuanced perspective on the circumstances under which the use of post-hoc explanatory methods is justified. Namely, when a '*transparency-by-design*' approach with traditional linear regression is not sufficient to solve HRM prediction tasks, the translation of complex ML models into human-understandable visualisations is required. As theoretical implications, this paper suggests that we can only fully understand the multi-layered HR explained to us by real-world data if we incorporate ML-based inductive methods together with traditional deductive methods.	

[1] https://www.vhbonline.org/fileadmin/vhb/Services/vhb-rating/PERS/VHB_Rating_2024_Area_rating_PERS.pdf (retrieved on July 7, 2025).
[2] Average number of citations per article in the first two years; https://www.tandfonline.com/journals/rijh20/about-this-journal#aims-and-scope (retrieved on July 23, 2025).
[3] Average number of citations per article over the last four years; https://www.tandfonline.com/journals/rijh20/about-this-journal#aims-and-scope (retrieved on July 23, 2025).
[4] Evaluation of journals based on their scientific influence (considering citation analysis and journal prestige); https://www.scimagojr.com/journalsearch.php?q=24840&tip=sid&clean=0 (retrieved on July 7, 2025).

Table 4: Publication details study two

Study no.	**2**
Title	**Exploring the Individual Adoption of Human Resource Analytics: Behavioural Beliefs and the Role of Machine Learning Characteristics**
Co-Authors	Christian Ertel, Ansgar Heidemann
Research Approach	Empirical-qualitative, interviews
Publication Status	Published
Journal	Technological Forecasting & Social Change
Journal Metrics	Journal-Ranking (VHB-Rating 2024)[5]: B Journal Impact Factor 2024[6]: 13.3 Journal CiteScore 2024[7]: 26.3 SCImago Journal Rank 2024[8]: 3.472 (Quartile 1)
Presentations	- 2nd EIASM Workshop on People Analytics and Algorithmic Management (PAAM), Leeds (U.K.) - Research Seminar University of Twente 2022, Enschede (Netherlands) - Berens Doctoral Seminar 2023, Bochum (Germany)
Summary	The technological capabilities of Human Resource Analytics (HRA), enhanced by recent innovations in Machine Learning (ML), offer exciting opportunities. However, organisations often fail to realise these potentials because of a limited understanding of why individuals choose to adopt or disregard respective tools. Prior research on innovation adoption offers preliminary insights but fails to aggregate the determinants of individual adoption into actionable suggestions for decisions in the ML adoption process. Our study applies focused interviews to examine non-ML experts' reasoning for using a specific tool tailored to a public sector organisation, which corresponds to the usual end-user perspective of ML-based HRA adoption. By drawing from the HRA adoption framework, provided by Vargas et al. (2018), we contribute to the literature by identifying relevant beliefs and experiences influencing one's intention to adopt ML-based HRA and by qualitatively linking these beliefs to ML characteristics such as transparency, automation and fairness. For practitioners, we provide actionable guidance emphasising the need to ensure fairness proactively, as interviewees do not consider this aspect when deciding to adopt ML-based HRA.

[5] https://www.vhbonline.org/fileadmin/vhb/Services/vhb-rating/TIE/VHB_Rating_2024_Area_rating_TIE.pdf (retrieved on July 7, 2025).
[6] Average number of citations per article in the first two years; https://www.sciencedirect.com/journal/technological-forecasting-and-social-change (retrieved on July 7, 2025).
[7] Average number of citations per article over the last four years; https://www.sciencedirect.com/journal/technological-forecasting-and-social-change (retrieved on July 7, 2025).
[8] Evaluation of journals based on their scientific influence (considering citation analysis and journal prestige); https://www.scimagojr.com/journalsearch.php?q=14704&tip=sid&clean=0 (retrieved on July 7, 2025).

Table 5: Publication details study three

Study no.	**3**
Title	**Turning the Tide: Typologies of Temporary Managers in HR Decision-Making During Crises**
Co-Authors	Laura J. Packheiser
Research Approach	Empirical-qualitative, interviews
Publication Status	Manuscript under Review, submitted in June 2025
Journal	Schmalenbach Journal of Business Research (SBUR)
Journal Metrics	Journal-Ranking (VHB-Rating 2024)[9]: B SCImago Journal Rank 2024[10]: 0.524 (Quartile 2)
Presentations	- Brown Bag University of Alberta 2025, Edmonton (Canada) - 40th EIASM Workshop on Strategic Human Resource Management, Fribourg (Switzerland)
Summary	In an increasingly volatile and uncertain business environment, organisations are turning to temporary managers, often referred to as interim managers, with greater frequency to navigate periods of crisis and transformation. Moreover, the successful management of crises is closely associated with skilful human resources (HR) decisions, which are characterised as uniquely complex, sensitive and simultaneously impactful. By virtue of their external status and limited tenure, temporary managers can make impartial and sometimes radical HR decisions without the burden of long-term internal consequences. However, they also face specific challenges, particularly in establishing authority and legitimacy within the organisation. This study explores the human capital that temporary managers contribute in crisis contexts, with a particular focus on their daily tasks, decision-making processes, and competency profiles. Drawing on a qualitative research design involving in-depth interviews with seventeen temporary managers, the analysis identifies three distinct typologies*: The Decider*, *The Advisor*, and *The Realiser*. These typologies reflect differentiated strategic orientations and align with Henry Mintzberg's framework for managerial roles. Thus, this study sheds light on the various strategic approaches that temporary managers employ to restore an organisation's profitability during crises, contributing to a broader understanding of the human capital that managers bring to organisations. Moreover, the findings extend Mintzberg's framework by incorporating human capital dimensions – namely, task structure, decision logic, and competence – into the role conceptualisation of temporary managers.

[9] https://www.vhbonline.org/fileadmin/vhb/Services/vhb-rating/STRAT/VHB_Rating_2024_Area_rating_STRAT.pdf (retrieved on July 7, 2025).
[10] Evaluation of journals based on their scientific influence (considering citation analysis and journal prestige); https://www.scimagojr.com/journalsearch.php?q=58834&tip=sid&clean=0 (retrieved on July 7, 2025).

1.4 List of References

Aguinis, Herman; Beltran, Jose R.; Cope, Amando (2024): How to Use Generative AI as a Human Resource Management Assistant. In: Organizational Dynamics 53 (1), p. 101029. DOI: 10.1016/j.orgdyn.2024.101029.

Alam, Shafiq; Dong, Zhan; Kularatne, Zhan; Rashid, Muhammad S. (2025): Exploring Approaches to Overcome Challenges in Adopting Human Resource Analytics through Stakeholder Engagement. In: Management Review Quarterly. DOI: 10.1007/s11301-025-00491-y.

Alon-Barkat, Saar; Busuioc, Madalina (2023): Human–AI Interactions in Public Sector Decision Making: "Automation Bias" and "Selective Adherence" to Algorithmic Advice. In: Journal of Public Administration Research and Theory 33 (1), pp. 153–169. DOI: 10.1093/jopart/muac007.

Amazon (2025): What We Do – Artificial Intelligence (AI). Available online at: https://www.aboutamazon.com/what-we-do/artificial-intelligence-ai (retrieved on July 7, 2025).

Angrave, David; Charlwood, Andy; Kirkpatrick, Ian; Lawrence, Mark; Stuart, Mark (2016): HR and Analytics: Why HR Is Set to Fail the Big Data Challenge. In: Human Resource Management Journal 26 (1), pp. 1–11. DOI: 10.1111/1748-8583.12090.

Aral, Sinan; Brynjolfsson, Erik; Wu, Lynn (2012): Three-Way Complementarities: Performance Pay, Human Resource Analytics, and Information Technology. In: Management Science 58 (5), pp. 913–931. DOI: 10.1287/mnsc.1110.1460.

Bahuguna, Prakash C.; Srivastava, Rajeev; Tiwari, Saurabh (2023): Human Resources Analytics: Where Do We Go from Here? In: Benchmarking 31 (2), pp. 640–668. DOI: 10.1108/BIJ-06-2022-0401.

Böhmer, Nicole; Schinnenburg, Heike (2023): Critical Exploration of AI-Driven HRM to Build up Organizational Capabilities. In: Employee Relations 45 (5), pp. 1057–1082. DOI: 10.1108/ER-04-2022-0202.

Bosch (2025): Manufacturing: Data Empowers Manufacturers with Improved Efficiency and Machine Yield. Available online at: https://bosch-softwaretechnologies.com/en/services/enterprise-services/ai-and-big-data/manufacturing (retrieved on July 7, 2025).

van den Broek, Elmira; Sergeeva, Anastasia; Huysman Vrije, Marleen (2021): When the Machine Meets the Expert: An Ethnography of Developing AI for Hiring. In: MIS Quarterly 45 (3), pp. 1557–1580. DOI: 10.25300/MISQ/2021/16559.

Brynjolfsson, Erik; Hitt, Lorin M.; Kim, Heekyung Hellen (2011): Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? In: SSRN Electronic Journal. DOI: 10.2139/ssrn.1819486.

Budhwar, Pawan; Chowdhury, Soumyadeb; Wood, Geoffrey; Aguinis, Herman; Bamber, Greg J.; Beltran, Jose R.; Boselie, Paul; Lee Cooke, Fang; Decker, Stephanie; DeNisi, Angelo; Dey, Prasanta Kumar; Guest, David; Knoblich, Andrew J.; Malik, Ashish; Paauwe, Jaap; Papagiannidis, Savvas; Patel, Charmi; Pereira, Vijay; Ren, Shuang; Rogelberg, Steven; Saunders, Mark N. K.; Tung, Rosalie L.; Varma, Arup (2023): Human Resource Management in the Age of Generative Artificial Intelligence: Perspectives and Research Directions on ChatGPT. In: Human Resource Management Journal 33 (3), pp. 606–659. DOI: 10.1111/1748-8583.12524.

Charlwood, Andy; Guenole, Nigel (2022): Can HR Adapt to the Paradoxes of Artificial Intelligence? In: Human Resource Management Journal 32 (4), pp. 729–742. DOI: 10.1111/1748-8583.12433.

Chowdhury, Soumyadeb; Dey, Prasanta; Joel-Edgar, Sian; Bhattacharya, Sudeshna; Rodriguez-Espindola, Oscar; Abadie, Amelie; Truong, Linh (2023a): Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework. In: Human Resource Management Review 33 (1), p. 100899. DOI: 10.1016/j.hrmr.2022.100899.

Chowdhury, Soumyadeb; Joel-Edgar, Sian; Dey, Prasanta Kumar; Bhattacharya, Sudeshna; Kharlamov, Alexander (2023b): Embedding Transparency in Artificial Intelligence Machine Learning Models: Managerial Implications on Predicting and Explaining Employee Turnover. In: The International Journal of Human Resource Management 34 (14), pp. 1–32. DOI: 10.1080/09585192.2022.2066981.

Coco, Cedric T.; Jamison, Fiona; Black, Heather (2011): Connecting People Investments and Business Outcomes at Lowe's: Using Value Linkage Analytics to Link Employee Engagement to Business Performance. In: Human Resource Planning 34 (2), pp. 28–34.

Coolen, Patrick; van den Heuvel, Sjoerd; van de Voorde, Karina; Paauwe, Jaap (2023): Understanding the Adoption and Institutionalization of Workforce Analytics: A Systematic Literature Review and Research Agenda. In: Human Resource Management Review 33 (4), p. 100985. DOI: 10.1016/j.hrmr.2023.100985.

Dastin, Jeffrey (2022): Amazon Scraps Secret AI Recruiting Tool that Showed Bias Against Women. In: Martin, Kirsten (Ed.): Ethics of Data and Analytics. Boca Raton, Florida: Auerbach Publications, pp. 296–299. DOI: 10.1201/9781003278290-44.

Daugherty, Paul R.; Wilson, James; Chowdhury, Rumman (2018): Using Artificial Intelligence to Promote Diversity. In: MIT Sloan Management Review. Available online at: https://sloanreview.mit.edu/article/using-artificial-intelligence-to-promote-diversity (retrieved on July 7, 2025).

Davenport, Thomas H. (2013): Analytics 3.0. In: Harvard Business Review 91 (12), pp. 64–72.

Davenport, Thomas H. (2014): Big Data Work – Chancen Erkennen, Risiken Verstehen. München: Franz Vahlen.

Davenport, Thomas H.; Harris, J. G. (2007): Competing on Analytics: The New Science of Winning. In: Harvard Business Review Press 15 (217), pp. 24–27.

De Mauro, Andrea; Greco, Marco; Grimaldi, Michele (2016): A Formal Definition of Big Data based on its Essential Features. In: Library Review 65 (3), pp. 122–135. DOI: 10.1108/LR-06-2015-0061.

Delen, Dursun; Demirkan, Haluk (2013): Data, Information and Analytics as Services. In: Decision Support Systems 55 (1), pp. 359–363. DOI: 10.1016/j.dss.2012.05.044.

Diefenhardt, Felix; Rapp, Marco L.; Bader, Verena; Mayrhofer, Wolfgang (2024): 'In God We Trust. All Others Must Bring Data': Unpacking the Influence of Human Resource Analytics on the Strategic Recognition of Human Resource Management. In: Human Resource Management Journal. DOI: 10.1111/1748-8583.12583.

Duggan, James; Carbery, Ronan; McDonnell, Anthony; Sherman, Ultan (2023): Algorithmic HRM Control in the Gig Economy: The App-Worker Perspective. In: Human Resource Management 62 (6), pp. 883–899. DOI: 10.1002/hrm.22168.

Edwards, Martin R.; Charlwood, Andy; Guenole, Nigel; Marler, Janet (2022): HR Analytics: An Emerging Field Finding Its Place in the World alongside Simmering Ethical Challenges. In: Human Resource Management Journal 34 (2), pp. 326–336. DOI: 10.1111/1748-8583.12435.

Faraj, Samer; Pachidi, Stella; Sayegh, Karla (2018): Working and Organizing in the Age of the Learning Algorithm. In: Information and Organization 28 (1), pp. 62–70. DOI: 10.1016/j.infoandorg.2018.02.005.

Fernandez, Vicenc; Gallardo-Gallardo, Eva (2021): Tackling the HR Digitalization Challenge: Key Factors and Barriers to HR Analytics Adoption. In: Competitiveness Review 31 (1), pp. 162–187. DOI: 10.1108/CR-12-2019-0163.

Gal, Uri; Jensen, Tina Blegind; Stein, Mari-Klara (2020): Breaking the Vicious Cycle of Algorithmic Management: A Virtue Ethics Approach to People Analytics. In: Information and Organization 30 (2), p. 100301. DOI: 10.1016/j.infoandorg.2020.100301.

GDPR (2016): Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data, and Repealing Directive 95/46/EC (General Data Protection Regulation), OJ L 119, 4.5.2016, pp. 1–88.

Giermindl, Lisa Marie; Strich, Franz; Christ, Oliver; Leicht-Deobald, Ulrich; Redzepi, Abdullah (2022): The Dark Sides of People Analytics: Reviewing the Perils for Organisations and Employees. In: European Journal of Information Systems 31 (3), pp. 410–435. DOI: 10.1080/0960085X.2021.1927213.

Guenole, Nigel; Feinzig, Sheri; Ferrar, Jonathan; Allden, Joanne (2015): Starting the Workforce Analytics Journey – The Tirst 100 Days. In: IBM Smarter Workforce Institute. Available online at: https://www.elearninglearning.com/taurus/media/elearning/whitepapers/IBM-Workforce.PDF (retrieved on July 7, 2025).

Haenlein, Michael; Kaplan, Andreas (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. In: California Management Review 61 (4), pp. 5–14. DOI: 10.1177/0008125619864925.

Hamilton, R. H.; Sodeman, William A. (2020): The Questions We Ask: Opportunities and Challenges for Using Big Data Analytics to Strategically Manage Human

Capital Resources. In: Business Horizons 63 (1), pp. 85–95. DOI: 10.1016/j.bushor.2019.10.001.

Harris, Jeanne G.; Craig, Elizabeth; Light, David A. (2011): Talent and Analytics: New Approaches, Higher ROI. In: Journal of Business Strategy 32 (6), pp. 4–13. DOI: 10.1108/02756661111180087.

Hunkenschroer, Anna L.; Luetge, Christoph (2022): Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. In: Journal of Business Ethics 178 (3), pp. 977–1007. DOI: 10.1007/s10551-022-05049-6.

King, Kylie G. (2016): Data Analytics in Human Resources: A Case Study and Critical Review. In: Human Resource Development Review 15 (4), pp. 487–495. DOI: 10.1177/1534484316675818.

Kryscynski, David; Reeves, Cody; Stice-Lusvardi, Ryan; Ulrich, Michael; Russell, Grant (2018): Analytical Abilities and the Performance of HR Professionals. In: Human Resource Management 57 (3), pp. 715–738. DOI: 10.1002/hrm.21854.

Langer, Markus; Landers, Richard N. (2021): The Future of Artificial Intelligence at Work: A Review on Effects of Decision Automation and Augmentation on Workers Targeted by Algorithms and Third-Party Observers. In: Computers in Human Behavior 123, p. 106878. DOI: 10.1016/j.chb.2021.106878.

Margherita, Alessandro (2022): Human Resources Analytics: A Systematization of Research Topics and Directions for Future Research. In: Human Resource Management Review 32 (2), p. 100795. DOI: 10.1016/j.hrmr.2020.100795.

Marler, Janet H.; Boudreau, John W. (2017): An Evidence-based Review of HR Analytics. In: The International Journal of Human Resource Management 28 (1), pp. 3–26. DOI: 10.1080/09585192.2016.1244699.

McCartney, Steven; Fu, Na (2022a): Bridging the Gap: Why, How and When HR Analytics Can Impact Organizational Performance. In: Management Decision 60 (13), pp. 25–47. DOI: 10.1108/MD-12-2020-1581.

McCartney, Steven; Fu, Na (2022b): Promise versus Reality: A Systematic Review of the Ongoing Debates in People Analytics. In: Journal of Organizational Effectiveness 9 (2), pp. 281–311. DOI: 10.1108/JOEPP-01-2021-0013.

Meijerink, Jeroen; Bondarouk, Tanya (2023): The Duality of Algorithmic Management: Toward a Research Agenda on HRM Algorithms, Autonomy and Value Creation.

In: Human Resource Management Review 33 (1), p. 100876. DOI: 10.1016/j.hrmr.2021.100876.

Meijerink, Jeroen; Boons, Mark; Keegan, Anne; Marler, Janet (2021): Algorithmic Human Resource Management: Synthesizing Developments and Cross-Disciplinary Insights on Digital HRM. In: The International Journal of Human Resource Management 32 (12), pp. 2545–2562. DOI: 10.1080/09585192.2021.1925326.

Minbaeva, Dana (2021): Disrupted HR? In: Human Resource Management Review 31 (4), p. 100820. DOI: 10.1016/j.hrmr.2020.100820.

Oswald, Frederick L.; Behrend, Tara S.; Putka, Dan J.; Sinar, Evan (2020): Big Data in Industrial-Organizational Psychology and Human Resource Management: Forward Progress for Organizational Research and Practice. In: Annual Review of Organizational Psychology and Organizational Behavior 7, pp. 505–533. DOI: 10.1146/annurev-orgpsych-032117-104553.

Pan, Yuan; Froese, Fabian; Liu, Ni; Hu, Yunyang; Ye, Maolin (2022). The Adoption of Artificial Intelligence in Employee Recruitment: The Influence of Contextual Factors. In: International Journal of Human Resource Management 33 (6), pp. 1125–1147. DOI: 10.1080/09585192.2021.1879206.

Pfeffer, Jeffrey; Veiga, John F. (1999): Putting People First for Organizational Success. In: Academy of Management Perspectives 13 (2), pp. 37–48. DOI: 10.5465/ame.1999.1899547.

Qamar, Yusra; Samad, Taab A. (2022): Human Resource Analytics: A Review and Bibliometric Analysis. In: Personnel Review 51 (1), pp. 251–283. DOI: 10.1108/PR-04-2020-0247.

Ramachandran, Rukma; Babu, Vimal; Murugesan, Vijaya P. (2023): Human Resource Analytics Revisited: A Systematic Literature Review of Its Adoption, Global Acceptance and Implementation. In: Benchmarking 31 (7), pp. 2360–239. DOI: 10.1108/BIJ-04-2022-0272.

Ransbotham, Sam; Khodabandeh, Shervin; Kiron, David; Candelon, François; Chu, Michael; LaFountain, Burt (2020): Expanding AI's Impact with Organisational Learning. In: MIT Sloan Management Review and Boston Consulting Group. Available online at: https://sloanreview.mit.edu/projects/expanding-ais-impact-with-organizational-learning (retrieved on July 7, 2025).

Rasmussen, Thomas; Ulrich, Dave (2015): Learning from Practice: How HR Analytics Avoids Being a Management Fad. In: Organizational Dynamics 44 (3), pp. 236–242. DOI: 10.1016/j.orgdyn.2015.05.008.

Rombaut, Evy; Guerry, Marie-Anne (2018): Predicting Voluntary Turnover through Human Resources Database Analysis. In: Management Research Review 41 (1), pp. 96–112. DOI: 10.1108/MRR-04-2017-0098.

Samuel, Arthur L. (1959): Some Studies in Machine Learning Using the Game of Checkers. In: IBM Journal of Research and Development 3 (3), pp. 210–229. DOI: 10.1147/rd.33.0210.

Schaefer, Cindy; Lemmer, Kristina; Samy Kret, Kret; Ylinen, Maija; Mikalef, Patrick; Niehaves, Bjoern (2021): ”Truth or Dare?” – How Can We Influence the Adoption of Artificial Intelligence in Municipalities? In: Proceedings of the 54th Hawaii International Conference on System Sciences, pp. 2347–2356. Maui, Hawaii.

Shah, Naimatullah; Irani, Zahir; Sharif, Amir M. (2017): Big Data in an HR Context: Exploring Organizational Change Readiness, Employee Attitudes and Behaviors. In: Journal of Business Research 70, pp. 366–378. DOI: 10.1016/j.jbusres.2016.08.010.

Shamim, Saqib; Zeng, Jing; Shariq, Syed Muhammad; Khan, Zaheer (2019): Role of Big Data Management in Enhancing Big Data Decision-Making Capability and Quality among Chinese Firms: A Dynamic Capabilities View. In: Information and Management 56 (6), p. 103135. DOI: 10.1016/j.im.2018.12.003.

Shet, Sateesh. V.; Poddar, Tanuj; Wamba Samuel, Fosso; Dwivedi, Yogesh K. (2021): Examining the Determinants of Successful Adoption of Data Analytics in Human Resource Management – A Framework for Implications. In: Journal of Business Research 131 (C), pp. 311–326. DOI: 10.1016/j.jbusres.2021.03.054.

Simbeck, Katharina (2019): HR Analytics and Ethics. In: IBM Journal of Research and Development 63 (4–5), p. 9. DOI: 10.1147/JRD.2019.2915067.

Speer, Andrew B. (2021): Empirical Attrition Modelling and Discrimination: Balancing Validity and Group Differences. In: Human Resource Management Journal 34 (1), pp. 1–19. DOI: 10.1111/1748-8583.12355.

Strich, Franz; Mayer, Anne-Sophie; Fiedler, Marina (2021): What Do I Do in a World of Artificial Intelligence? Investigating the Impact of Substitutive Decision-Making

AI Systems on Employees' Professional Role Identity. In: Journal of the Association for Information Systems 22 (2), pp. 304–324. DOI: 10.17705/1jais.00663.

Strohmeier, Stefan; Piazza, Franca (2015): Artificial Intelligence Techniques in Human Resource Management – A Conceptual Exploration. In: Kahraman, Cengiz; Çevik Onar, Sezi (Eds.): Intelligent Techniques in Engineering Management (Intelligent Systems Reference Library Book 87). Cham: Springer, pp. 149–172. DOI: 10.1007/978-3-319-17906-3_7.

Thakral, Priyanka; Srivastava, Praveen R.; Dash, Sanket S.; Jasimuddin, Sajjad M.; Zhang, Zuopeng J. (2023): Trends in the Thematic Landscape of HR Analytics Research: A Structural Topic Modeling Approach. In: Management Decision 61 (12), pp. 3665–3690. DOI: 10.1108/MD-01-2023-0080.

Theres, Christian; Strohmeier, Stefan (2024): Consolidating the Theoretical Foundations of Digital Human Resource Management Acceptance and Use Research: A Meta-Analytic Validation of UTAUT. In: Management Review Quarterly 74, pp. 2683–2715. DOI: 10.1007/s11301-023-00367-z.

Tursunbayeva, Aizhan; Di Lauro, Stefano; Pagliari, Claudia (2018): People Analytics – A Scoping Review of Conceptual Boundaries and Value Propositions. In: International Journal of Information Management 43, pp. 224–247. DOI: 10.1016/j.ijinfomgt.2018.08.002.

Tursunbayeva, Aizhan; Pagliari, Claudia; Di Lauro, Stefano; Antonelli, Gilda (2022): The Ethics of People Analytics: Risks, Opportunities and Recommendations. In: Personnel Review 51 (3), pp. 900-921. DOI: 10.1108/PR-12-2019-0680.

Uber (2018): Uber's Big Data Platform: 100+ Petabytes with Minute Latency. Available online at: https://uber.com/en-CA/blog/uber-big-data-platform (retrieved on July 7, 2025).

Ulrich, Dave; Dulebohn, James H. (2015): Are We There Yet? What's Next for HR? In: Human Resource Management Review 25 (2), pp. 188–204. DOI: 10.1016/j.hrmr.2015.01.004.

Vargas, Roslyn; Yurova, Yuliya V.; Ruppel, Cynthia P.; Tworoger, Leslie C.; Greenwood, Regina (2018): Individual Adoption of HR Analytics: A Fine Grained View of the Early Stages Leading to Adoption. In: The International Journal of Human Resource Management 29 (22), pp. 3046–3067. DOI: 10.1080/09585192.2018.1446181.

Wirtz, Bernd W.; Langer, Paul F.; Fenner, Carolina (2021): Artificial Intelligence in the Public Sector – A Research Agenda. In: International Journal of Public Administration 44 (13), pp. 1103–1128. DOI: 10.1080/01900692.2021.1947319.

2 Machine Learning with Real-World HR Data: Mitigating the Trade-Off between Predictive Performance and Transparency

2.1 Publication Details

Abstract:

Machine Learning (ML) algorithms offer a powerful tool for capturing multifaceted relationships through inductive research to gain insights and support decision-making in practice. This study contributes to understanding the dilemma whereby the more complex ML becomes, the more its value proposition can be compromised by its opacity. Using a longitudinal dataset on voluntary employee turnover from a German federal agency, we provide evidence for the underlying trade-off between predictive performance and transparency for ML, which has not been found in similar Human Resource Management (HRM) studies using artificially simulated datasets. We then propose measures to mitigate this trade-off by demonstrating the use of post-hoc explanatory methods to extract local (employee-specific) and global (organisation-wide) predictor effects. After that, we discuss their limitations, providing a nuanced perspective on the circumstances under which the use of post-hoc explanatory methods is justified. Namely, when a '*transparency-by-design*' approach with traditional linear regression is not sufficient to solve HRM prediction tasks, the translation of complex ML models into human-understandable visualisations is required. As theoretical implications, this paper suggests that we can only fully understand the multi-layered HR explained to us by real-world data if we incorporate ML-based inductive methods together with traditional deductive methods.

Co-Authors: Ansgar Heidemann, Michael Tekieli

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2.2 Introduction

ML algorithms are increasingly used in HRM research to reveal and explain multifaceted phenomena beyond linearity from data, known as an '*ML-based inductive*' research method (for an example relating to employee turnover prediction, see King 2016; Rombaut and Guerry 2018, 2021, Choudhury et al. 2021, Erel et al. 2021, Speer 2021, Yuan et al. 2021, Chowdhury et al. 2022). This method promises to objectively translate large amounts of raw data into new information provided by otherwise overlooked, complicated interactions between predictors with a level of efficiency not achieved by humans (van den Broek et al. 2021). Generally, this explanatory approach requires neither prior assumptions nor explicit hypotheses, which opens up various opportunities for HR research and practice (Choudhury et al. 2021). Thus, the ML-based inductive research method enables the investigation of multifaceted relationships, to gain exploratory insights and develop theory (Putka et al. 2018; Cheng and Hackett 2021).

However, a challenge arises due to the complexity of ML algorithms, i.e. the disadvantage of not providing an easily understandable mathematical formula (Kellogg et al. 2020; Erel et al. 2021). High ML model complexity occurs when an ML algorithm capable of modelling flexible functions beyond linearity (*Neural Networks*, *Random Forest*, etc.) is applied to a large dataset with multifaceted relationships (Choudhury et al. 2021). Complex models achieve high predictive performance, which is the extent of the ML model to solve a prediction task, depending on its context and goal, with different statistical measures (e.g. root-mean-squared error for regression, accuracy for classification). Nevertheless, complex models remain opaque, in that (a) predictors are not understandable (e.g. coming from a complex system itself), (b) relationships between predictors and predictions are hidden and (c) no explanation for a specific prediction is given (Burrell 2016; Langer and König 2023).

Simply, there are two sides to a continuum: opacity is a lack of understanding regarding the inner workings of the ML model, while transparency is understanding the relationships between predictors and predictions (Langer and König 2023). To ascertain the position on this continuum between transparency and opacity, ML algorithm selection is a pivotal determinant. For example, a linear regression model can be considered as inherently transparent, also known as the '*transparency-by-design*' approach, because the mechanisms of the mathematical formulas and their parameters, which affect the relationships between predictors and predictions, are interpretable. Generally, it is known that the trade-off between predictive performance and transparency in ML models goes hand in hand with their complexity (Arrieta et al. 2020, p. 100), but it has not been empirically demonstrated or investigated in real-world HRM applications. Thus, we ask:

> **RQ1:** To what extent does ML in real-world HRM applications face trade-offs between predictive performance and transparency?

We select employee turnover prediction as a representative ML application in HR. This has also recently been investigated in two closely related studies (Choudhury et al. 2021; Chowdhury et al. 2022). We extend these studies by providing an empirical example of the trade-off between predictive performance and transparency in real-world data that was not found using artificially simulated datasets used in either study. Also, like these studies, we apply multiple post-hoc explanatory methods to mitigate the aforementioned trade-off. These methods aim to explain elements of a complex ML model while, such as the influence importance of predictors, maintaining its high predictive performance, which increases its transparency. However, additionally we critique the limitations and ask about the appropriate circumstances for using post-hoc explanatory methods:

> **RQ2:** Under what circumstances, may post-hoc explanatory methods be applied to understand the rationale behind complex ML model predictions?

By answering these research questions, we contribute to the literature by (1) empirically demonstrating and discussing the consequences of the trade-off between predictive performance and transparency, (2) providing a nuanced perspective when the use of post-hoc explanatory methods is justified due to lack of alternatives (3) and outlining the possibilities of revealing the multifaceted effects of complex ML model predictors combined with post-hoc explanatory methods. Thus, we respond to research calls to investigate when and how organisations can switch from opaque to transparent ML (Chowdhury et al. 2022, p. 25). As a theoretical implication, our study exemplifies the need for an inductive method based on ML, given the complexity of real-world HR phenomena that cannot be investigated to the same depth using traditional methods such as linear regression. However, caution is needed when interpreting and deriving implications, as the available post-hoc explanatory methods required for complex models can be misleading. Confirmatory studies with deductive evidence may therefore be complementarily necessary.

The paper is organised as follows. The second section reviews the literature on the multifaceted causes of employee turnover, frameworks for ML-based inductive research methods and the trade-off in ML complexity. The third section summarises the methodology used and presents the empirical dataset. The fourth section presents the results and applies three post-hoc explanatory methods to mitigate a trade-off. Finally, the fifth and sixth sections discuss post-hoc explanatory methods before concluding.

2.3 Literature Review

2.3.1 Turnover Causes Are Multifaceted

Employee turnover prediction is selected as a representative ML application in HRM because turnover is generally an intricate process (Yuan et al. 2021) resulting from a series of possible sequences of events or '*pathways*' (Russell and Sell 2012, p. 126). Consequently, the literature lists numerous predictors directly influencing employee turnover (e.g. Holtom et al. 2008; Rubenstein et al. 2018). This suggests that turnover is more complex than the largely linear relationships previously studied. However, turnover causes are likely to be nonlinear, with the nature of these relationships between variables changing at different points (e.g. U-shaped), or heterogeneous with different relationships for different subgroups of employees. For example, Gray and Phillips (1994) find a U-shaped relationship between age and turnover, implying that turnover is high among young employees and decreases with age; thereafter, turnover gradually increases again, due to retirement. A negative correlation between tenure and employee turnover is widespread (Rubenstein et al. 2018). Furthermore, Grissom et al. (2016) find a negative relation between salary predictors (total/increase) and turnover in public administration, albeit up to a certain level, whereas turnover at the managerial level might work differently. Lin et al. (2021) emphasise that wage increases significantly reduce voluntary turnover. In addition, they examine the moderating effect on the relationship between wage increases and turnover, finding a significant negative relationship in this regard, albeit only for workers with longer tenure.

In summary, the sophistication of relationships leading to employee turnover is not only caused by linear relationships between several predictors and turnover, but also nonlinearity and heterogeneity in employee subgroups, which lead to mathematical interactions among predictors.

2.3.2 Increasing Algorithm Complexity

Multifaceted employee turnover prediction phenomena contradict implicit assumptions of linearity in traditional ordinary least squares models, thereby strengthening the rationale for using ML for prediction and knowledge (Erel et al. 2021). Recent literature presents frameworks and proposals for inductive research methods that introduce the principles of modern predictive models (Yuan et al. 2021) and common algorithms (Putka et al. 2018), to embedded ML in scientific methodologies. For example, ML algorithms used for employee turnover prediction include *Random Forest* (Choudhury et al. 2021; Speer 2021), *Extreme Gradient Boosting* (Erel et al. 2021) and *Gradient Boosting Machines* (King 2016). These so-called '*ensemble*' algorithms combine hundreds of heterogeneous trees, each of which automatically selects relevant predictors and their weights, groups data into relevant subregions and finds local dependencies (Putka et al. 2018). Similarly, increasing the number of neurons per layer or the number of layers in a neural network leads to what are known as deep learning algorithms that can achieve the same result (Vale et al. 2022).

To avoid system-based ML opacity resulting from increasing complexity, knowledge about algorithms is insufficient, as the amount of information causes information fatigue and meaninglessness (Gal et al. 2020). Complex ML algorithms learn by building their representation of a decision without considering human comprehension, thereby escaping human understanding (Burrell 2016; Kellogg et al. 2020, p. 372). In contrast to traditional statistical and econometric approaches, non-parametric ML algorithms do not provide a representative mathematical formula that can be easily understood (Erel et al. 2021, p. 3229). However, some do provide other representations that are understandable to humans, such as the rule system of Classification Trees or the conditional probabilities of Naïve Bayes Classifiers (Arrieta et al. 2020). This means, the decision between a more transparent, simple ML algorithm and a more complex, opaque one is more of a continuum due to the variety of algorithm options available (Langer and König 2023). Regardless of the specific algorithm, it is widely assumed that higher ML model complexity directly correlates with higher prediction performance, or expressed differently, solves the prediction task more effectively. Interestingly, this is not necessarily the case, as it depends on the specific prediction task and the flexibility required to approximate the underlying data, in particular the amount available and its distribution among the variables' values (Rudin 2019).

2.3.3 Challenges Arising from Algorithm Opacity

HRM is a high-stakes decision-making environment because individuals are directly affected, and data-driven decisions have various ethical and legal consequences (Gal et al. 2020). To verify fairness and nondiscrimination, input data, data analysis procedures and the links between results and conclusions must be transparent so that predictions can be validated. One reason is that correlations can be established but causal relationships are not implied. Opaque algorithms jeopardise the ability to test for adverse impacts by challenging differences between groups with existing evidence (Meijerink et al. 2021, p. 2549; Charlwood and Guenole 2022, p. 7), thus hampering unavoidable critical thinking about predictive composites, causal inferences and subgroup differences (Putka et al. 2018, p. 711).

ML transparency is important not only for practical applications, but also for researchers who want to understand, for example, what nonlinear effects independent variables have. Somers et al. (2021) challenge the linear assumptions of HR theory regarding employee well-being and demonstrate the use of complex ML models such as neural networks to detect nonlinearities. The tools used, such as three-dimensional visualisation, help uncover the existence of nonlinear phenomena but do not provide sufficient transparency to extract explicit relationships or to include more than two predictors (Somers et al. 2021). Yuan et al. (2021) use ML to identify the key predictors of employee turnover in a sample of *Small and Medium-Sized Enterprises* (SMEs). However, because of the algorithm's opacity, it is vague how the predictors affect turnover. For example, perceived unfairness is the most important predictor, but it is unclear at what point perceived unfairness triggers turnover.

In summary, it is essential to the success of ML in HR applications to (1) disclose how an algorithm makes a decision, (2) ensure the right to challenge an outcome and (3) provide expertise to address these challenges (Cheng and Hackett 2021). Ultimately, ML transparency is needed to increase trust in ML and question its responsible use (Chowdhury et al. 2022). In the absence of sufficient empirical examples, algorithm opacity is an important blind spot in algorithmic HRM research (Meijerink et al. 2021, p. 2550; Edwards et al. 2022, p. 5).

2.3.4 Tackling Algorithm Opacity with Technical Solutions

Research outside of HR has introduced methods to increase ML model transparency while maintaining high predictive performance, thus mitigating the aforementioned trade-off. *Explainable Artificial Intelligence* (XAI), also known as '*Interpretable ML*', is a rapidly evolving interdisciplinary research area offering multiple technical solutions (Arrieta et al. 2020; Molnar 2022). Moreover, XAI methods can be divided into either algorithmic models understandable to humans with appropriate knowledge (transparency-by-design), or methods using approximation to explain elements of complex – and thus opaque – models through simplified representations (post-hoc explanatory methods) (Arrieta et al. 2020; Langer and König 2023). Interestingly, documented applications of these technical solutions remain sparse in HR (Langer and König 2023), albeit the first examples are promising. Choudhury et al. (2021) demonstrate the use of global (enterprise-wide) post-hoc explanatory methods by applying feature importance methods and partial dependence plots to study nonlinear interactions between employee turnover and its predictors. Yakusheva et al. (2022) also use partial dependence plots to reveal an unexpected U-shaped relationship between higher staffing levels and the number of readmissions. Erel et al. (2021) provide an example of how to gain insights into opaque models of complex algorithms by quantifying the contribution of each predictor for director performance and turnover. Additionally, they demonstrate the existence of nonlinear and heterogenous relationships by breaking down the effects of predictors, using local post-hoc explanatory methods. In the HR literature, Chowdhury et al. (2022) use a local (employee-specific) post-hoc explanatory method for employee turnover prediction, called *Local Agnostic Model Explanations* (LIME).

2.3.5 Knowledge Gap

These examples show that post-hoc explanatory methods can be applied to complex ML models, improving our understanding of employee turnover causes. However, the proposed frameworks do not specify under what circumstances these methods should be used. One reason for this is the lack of a connection with the trade-off between predictive performance and transparency, which is not found in studies using artificially simulated datasets (Choudhury et al. 2021; Chowdhury et al. 2022). Instead, Choudhury et al. (2021) note that complex ML models (e.g. *Neural Networks, Random Forests*) offer only "*small performance increases over the baseline logistic regression*" and explain this marginal performance gain as "*meaningful interactions and nonlinearities among variables are* *only relevant for a small subset of the data*" (Choudhury et al. 2021, p. 48). Likewise, but independently, Chowdhury et al. (2022) come to a similar conclusion, as they find "*no significant differences*" in predictive performance between transparent and more complex algorithms (Chowdhury et al. 2022, p. 13). This warrants further investigation of the trade-off between predictive performance and transparency in practical, real-world HR datasets. The findings could serve as a basis for understanding the justified use of more complex, opaque ML algorithms and subsequent post-hoc explanatory methods.

2.4 Methodology

In turnover prediction, inductive research methods help analyse actual turnover in longitudinal data available through HR Information Systems (HRIS) (King 2016; Rombaut and Guerry 2018, 2021), also known as '*Attrition Modeling*' (Speer 2021). Building on these frameworks, we introduce a complete process for ML model development with addressing ML opacity depending on prediction task complexity. The post-hoc explanatory methods approximate a complex ML model and extract various explanations that provide the transparency needed to question the logic behind predictions. Figure 3 presents a schematic overview of an inductive research framework.

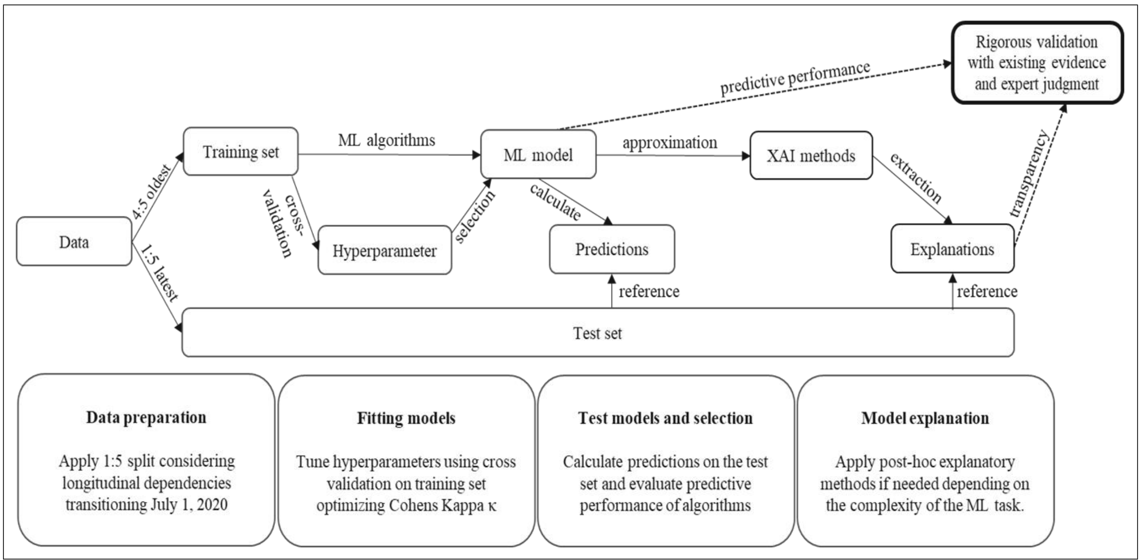

Figure 3: Inductive research process using machine learning with an out-of-sample test

2.4.1 Data Preparation

We adapt Rombaut and Guerry's (2018) inductive approach to predict actual voluntary employee turnover, using data from HRIS, and extend it by using complex ML algorithms and external predictors (Rombaut and Guerry 2018). The direct effect (black arrow) is examined by bridging several implicit established constructs, such as organisational commitment and payment satisfaction, thus taking a complementary approach to survey-based methods (see Figure 4).

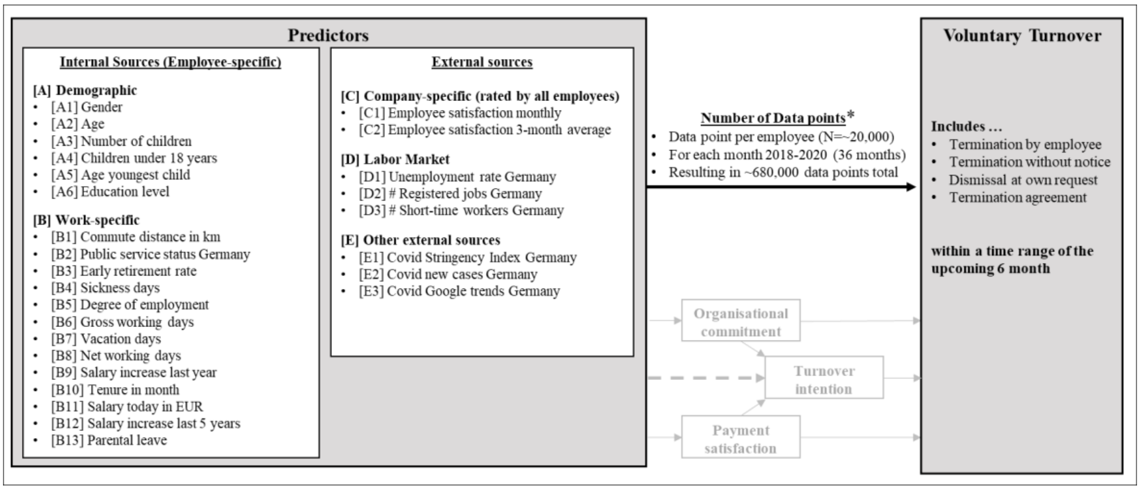

Figure 4: Acquired longitudinal data for historical voluntary turnover. The direct impact (black) is investigated in this study

The inductive ML methodology is based on a uniquely collected dataset of 680,000 data points from a German federal agency. Each row represents an employee in combination with a specific month and contains a dichotomous variable about whether they left the company in the six months following the observed month. This time horizon was chosen based on practical response time requirements for countermeasures; it is also consistent with other research (Speer 2021, p. 8). We used a data protection-approved process that builds on existing data agreements and anonymisation procedures during data collection.

The final dataset had 27 predictors (see Figure 4), most of which (19) originated from internal HR databases and are available for all 20,000 employees over 36 months. In addition, data on global employee satisfaction and external data were integrated into the dataset. Table 6 provides a basic descriptive statistical overview of the relevant variables. Please note that the low voluntary turnover rate (below 1%) is not unusual in the public sector (e.g. Grissom et al. 2016, p. 243), thereby making prediction particularly difficult (Kuhn 2019).

Table 6: Descriptive statistical overview of available variables in the acquired dataset

Nominal Variables	N (679,463)	Continuous Variables	Mean	Std. Dev.
A1_Gender		A2_Age	49.09	9.13
women	71.0%	A3_Number_of_children	1.13	0.94
men	25.7%	A5_Age_youngest_children	20.46	10.09
unknown	3.3%	B1_Commute_distance_in_km	15.28	17.62
		B3_Early_retirement_rate	6.08	17.12
A4_Children_under_18_years		B4_Sickness_days	2.07	4.73
0	72.6%	B5_Degree_of_employment	90.75	14.00
1	27.4%	B6_Gross_working_days	20.06	2.40
		B7_Vacation_days	2.33	3.55
A6_Education_level		B8_Net_working_days	15.34	5.78
lower degree		B9_Salary_increase_last_year	0.16	0.22
university	49.5%	B10_Tenure_in_month	272.17	127.18
vocational		B11_Salary_today_EUR	4068.64	889.97
training	46.7%	B12_Salary_increase_last_5 years	0.27	0.26
higher degree		B13_Parental_leave	0.06	1.11
university	3.8%	C1_Overall_employee_satisfaction	3.36	0.63
		C2_Employee_satisfation_moving_average	3.50	0.32
B2_Public_service_status_Germany		D1_Monthly_unemployment_rate_Germany	5.36	0.48
No	78.0%	D2_Monthly_number_of_vacacies_Germany	721.10	94.60
Yes	22.0%	D3_Monthly_short_time_workers_ Germany	1134.91	1659.11
		E1_Monthly_Covid_strigency_index_Germany	19.67	29.15
Voluntary turnover		E2_Monthly_New_Covid_Cases_Germany	69835.00	181549.00
No Turnover	**99.2%**	E3_Monthly_Covid_Google_trends_Germany	74.70	116.21
Turnover	**0.8%**			

2.4.2 Algorithm Selection

Table 7 summarises the selected algorithms chosen from common options used for employee turnover prediction (Chowdhury et al. 2022) or other inductive research (Putka et al. 2018). The advantage (transparency vs. performance) is drawn from the computer science literature, which order algorithms according to their comprehensible representational capabilities (Arrieta et al. 2020, p. 90).

Table 7: Selected ML algorithms with their primary advantage according to the transparency vs. performance trade-off

Algorithm	***R* base function/package**	**Advantage**
Generalised Linear Model	*glm*	Transparency
Elastic Net Regression	*glmnet*	Transparency
Classification Tree	*rpart2*	Transparency
Naïve Bayes	*naivebayes*	Transparency
Random Forest	*ranger*	Performance
Extreme Gradient Boosting	*xgbDart*	Performance
Generalised Boosted Machine	*gbm*	Performance
Feed Forward Neural Network	*nnet*	Performance

2.4.3 Fitting Models on Training Data

We use three-way partitioning by initially training several algorithms and their hyperparameters to optimise Cohen's Kappa κ on training and validation data (cross-validation on first 24 months between January 2018 and June 2020). Cohen's Kappa κ is a performance indicator that expresses the chance-adjusted proportion of correctly predicted outcomes (Cohen 1960). It varies between zero and one, providing an interpretation similar to the traditional *R-Squared Regression* (Yakusheva et al. 2022, p. 315). By optimising Cohen's Kappa κ instead of other common evaluation methods (e.g. Accuracy, *Receiver Operating Characteristic* = ROC), we are able to achieve higher predictive performance across all algorithms when tuning hyperparameters, as it is better suited to address the challenge of an imbalanced dataset (Kuhn 2019).

2.4.4 Evaluate Model Performance on Test Data

Evaluating the predictive performance of an ML model is critical to ensure the model's suitability for providing valuable insights. We test the predictive performance of each algorithm with out-of-sample test data (last six months between July 2020 and December 2020).

2.5 Results

2.5.1 Predictive Performance

The predictive performance measure results are reported in Table 8.

Table 8: Predictive performance measures of all used algorithms on test data

Algorithm	Advantage	*κ*	*ROC*	*Precision*	*Recall*
Random Forest*	Performance	**0.26***	0.87	0.18	0.54
Extreme Gradient Boosting	Performance	**0.24**	0.85	0.18	0.36
Generalised Boosted Machine	Performance	**0.22**	0.87	0.18	0.34
Classification Tree	Transparency	**0.18**	0.68	0.23	0.15
Feed Forwards Neural Network	Performance	**0.16**	0.68	0.17	0.16
Generalised Linear Model	Transparency	**0.12**	0.77	0.23	0.09
Elastic Net Regression	Transparency	**0.12**	0.76	0.20	0.09
Naïve Bayes	Transparency	**0.07**	0.59	0.05	0.23

We further compare the ML models with the highest predictive performance overall with the most successful algorithm (*Random Forest*), with the advantage of transparency (*Classification Tree*). The confusion matrices in Table 9 show the amount of cases on test data divided into positive and negative cases as well as correct and incorrect predictions.

Table 9: Confusion matrices on test data of Random Forest (highest predictive performance overall) and Classification Tree (most successful alternative algorithm with advantage transparency)

Random Forest			**Classification Tree**		
	Reference			Reference	
Prediction	*No Turnover*	*Turnover*	Prediction	*No Turnover*	*Turnover*
No Turnover	111,089 (96.60%)	513 (0.45%)	*No Turnover*	113,324 (98.53%)	940 (0.82%)
Turnover	2,800 (2.43%)	**598** (0.52%)	*Turnover*	565 (0.49%)	**171** (0.15%)

The Random Forest model successfully identifies 598 (= 52%) employee turnover cases. Overall, it provides a *fair* improvement over random guesses (κ = 0.26), according to common κ interpretation (Landis and Koch 1977). Measured by the recall (the ratio of true-positive cases to all positive cases) of 0.54, the model solves over half of the prediction task while providing sufficient precision (the ratio of true-positive cases to all positive predictions) of 0.18. Thus, given the challenge of highly imbalanced classes, due to the rarity of employee turnover cases, the difficult task of prediction is solved adequately, with an acceptable number of false-positive predictions.

The classification tree model successfully identifies 171 (= 15%) cases and provides a *slight* improvement over random guesses (κ = 0.18). The model successfully identifies 427 fewer cases of employee turnover than the Random Forest model. While the precision of 0.23 is slightly higher, the recall of 0.15 is significantly lower than the Random Forest. Hence, the majority of turnover cases are not detected, suggesting that the classification tree cannot predict diverse causes of employee turnover (Russell and Sell 2012, p. 126). The same applies to the other transparent ML models with even lower overall performance ($\kappa < 0.12$). The low predictive performance of the two linear models (*Generalised Linear Model*, *Elastic Net Regression*) indicates that linear assumptions might only be valid up to a certain extent.

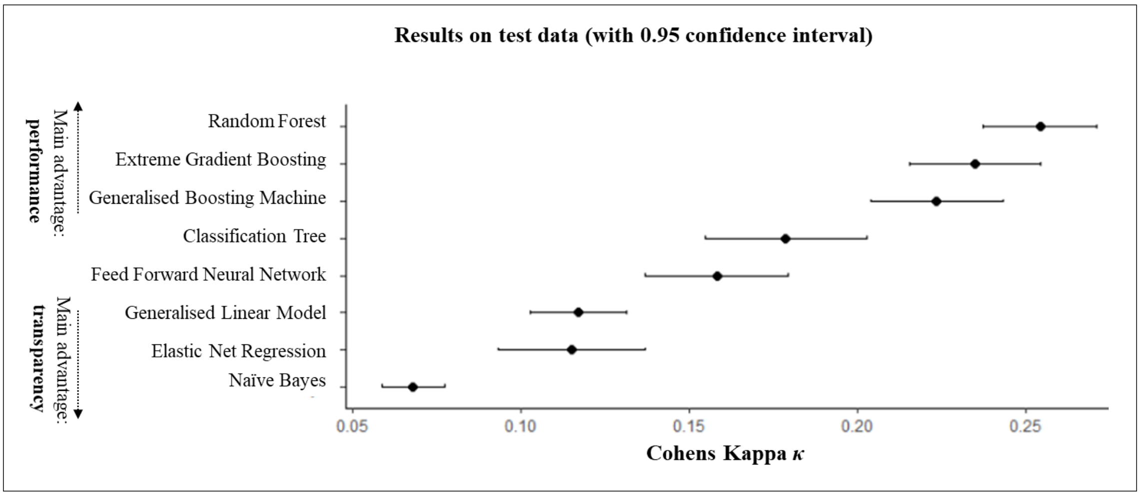

Figure 5: Predictive performance vs. transparency trade-off on test data (confidence interval 0.95)

Two findings emerge from these results. First, while all ML models can detect instances of employee turnover better than chance (κ > 0), they differ significantly in their predictive performance. Second, a trade-off between predictive performance and transparency is revealed, with more transparent algorithms achieving lower predictive performance (see Figure 5). The only exception – *Classification Trees* achieve higher performance than *Feed Forward Neural Networks* – is due to tree-based methods tending to outperform neural networks for tabular data (Shwartz-Ziv and Armon 2022). Consequently, XAI's transparency-by-design approach is not sufficient for identifying various nonlinear or heterogenous causes for employee turnover as the ML model cannot predict most turnover cases.

2.5.2 Applying Post-Hoc Explanatory Methods to Complex ML Models

Thus, we apply three popular post-hoc explanatory methods as the remaining options to gain insights from the Random Forest model. The choice of method from among numerous alternatives is beyond the scope of this study, so we refer the reader to the technical literature (e.g. Molnar 2022). All three methods are implemented with the R package '*IML*' (Interpretable ML) (Molnar et al. 2018).

2.5.2.1 Global Feature Importance

Global feature importance is extracted using the random permutation strategy, which determines the factor by which the model's classification error increases when feature values are randomly shuffled, thereby breaking the relationship between the feature and the true outcome (Molnar 2022).

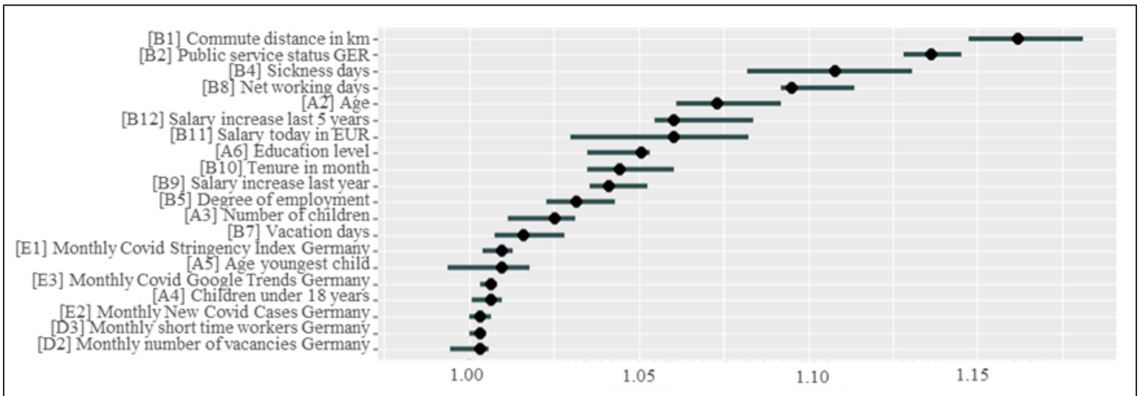

Figure 6: Permutated feature importance for the top 20 predictors (relative change in performance, confidence interval 0.95)

Figure 6 reveals that several demographic and work-specific predictors have the highest feature importance. *B1_commute_distance* and *B4_sickness_days* are among the top three features, consistent with other studies using data from the HRIS and finding them significant (Rombaut and Guerry 2021). External features generally have low feature importance but still contribute to predictive power. However, when comparing feature importance with other studies, it is important to note that results may vary depending on the features included in the dataset, the organisational context and changes over time (e.g. before and after Covid-19). A limitation of this high-level global feature importance method is that it is not suitable for examining whether the feature increases or decreases turnover risk.

2.5.2.2 Accumulated Local Effects

Accumulated Local Effects (ALE) describes how a single predictor influences prediction (strength, positive/negative contribution) on average, considering all employees in that local interval (Apley and Zhu 2020). Compared to alternative visualisation techniques on a global level (e.g. partial dependence plots), ALE is preferred when predictors correlate (Apley and Zhu 2020; Molnar 2022). Figure 7 highlights the ALE plots for the top 12 predictors, sorted by descending importance.

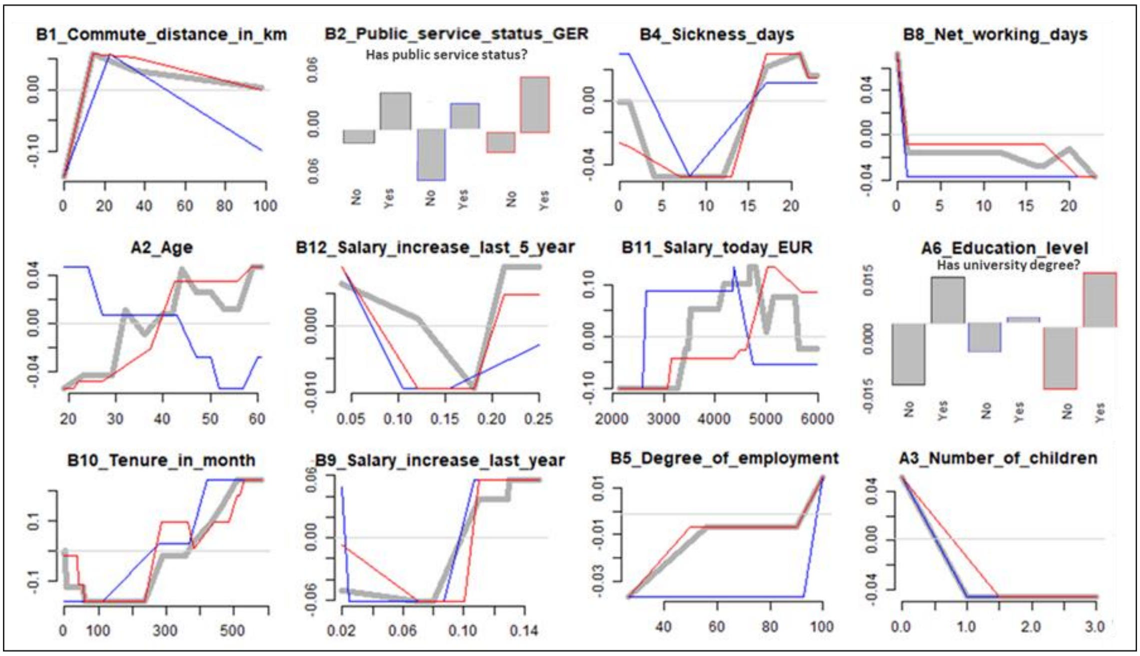

Figure 7: Accumulated local effect plots for the top 12 predictors according to permutated feature importance. Grey = all employees, blue = men, red = women

The ALE representation helps compare results with existing empirical evidence. Consistent with research, we first find a higher turnover probability for employees with a higher *commuting distance* (Rombaut and Guerry 2021), but there seems to be a threshold around 15 kilometres – after which turnover probability no longer increases but slowly decreases. Second, we find that high – especially complete – absenteeism is an early indicator of turnover, as reflected in the *sickness days* and *net working days* ALE plots (Rubenstein et al. 2018, p. 42).

Additionally, we find that turnover decreases for men in line with age; interestingly, turnover among women increases. Since women form the majority in the considered organisation, this also determines the direction for all employees. This chart clearly shows heterogeneity between subgroups. One HR manager cited extensive measures to retain young mothers as a particular reason for this phenomenon. Also interesting is that there is no negative correlation between *length of service* and turnover, which is widespread in the literature, indicating organisational particularity. Instead, we see a U-shaped turnover probability in relation to tenure. Overall, the *age* and *tenure* results support the finding that these relationships are not as clear-cut in practice as is often assumed (Gray and Phillips 1994, p. 825).

Altogether, the ALE results are mostly in line with current findings; however, they also reveal organisational particularities, nonlinear relationships and interactions between predictors. However, one criticism of ALE is that it can lead to unstable and inaccurate predictions due to collinearity between predictors in intervals where instances are rare (Molnar 2022).

2.5.2.3 Local Feature Effects

Finally, we apply *SHapley Additive exPlanations* (SHAP), a local post-hoc explanatory method computing the effect of each predictor at the employee-specific level (Lundberg and Lee 2017). SHAP's local approach is similar to its popular alternative LIME, in that it divides the complex ML model into several mathematical vicinities (Chowdhury et al. 2022). What distinguishes SHAP explanations from LIME and others is their additive nature due to the game-theoretic approach, which facilitates a simpler understanding. SHAP breaks down the probability of voluntary turnover for each employee into SHAP values that quantify increasing or decreasing effects. Ultimately, the sum of the SHAP values is the difference taken from the average predicted probability of turnover for all employees (Lundberg and Lee 2017; Erel et al. 2021). Figure 8 shows the relevant predictors with their values for two different employees, ordered by their additive explanatory contribution.

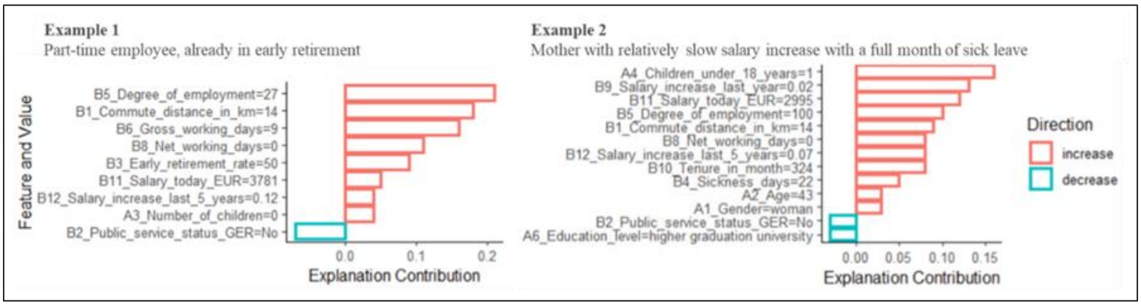

Figure 8: Top-10 SHAP values for two employees successfully predicted turnover candidates (true positive)

In Figure 8, a part-time employee (*Degree of employment* 27%, *Gross working days* 9) did not attend work in the last month for unknown reasons (*Net working days* 0). Together with the existing *early retirement rate* (50%) and salary-related predictors, this indicates a higher turnover risk. Interestingly, in this particular case, the *Salary today in EUR*

(3,781) and *Salary increase in the last 5 years* (12%) increase turnover probability, which is not clear in the ALE plots (Figure 7). Moreover, the explanatory contribution of *Tenure*, *Sickness days*, *Age* and *Education level* is relevant in example two but not in example one.

In summary, SHAP values at the individual (local) level for both examples are mostly consistent with ALE results. Nevertheless, a closer look at the local (employee-specific) compared to the global (company-wide) level offers more opportunities to challenge the results with existing evidence. The different selection of relevant predictors, as well as the contrary explanatory contribution, argues for interactions between predictors and different reasons for turnover in employee subgroups. Thus, our results support the rationale for using ML and post-hoc methods to study employee turnover (Erel et al. 2021, p. 3247). As discussed later, it should be noted that local post-hoc explanatory methods like SHAP are often criticised because their explanations might be unstable and can therefore provide (intentionally) misleading explanations (Ghassemi et al. 2021; Vale et al. 2022).

2.6 Discussion

The increasing complexity of ML-based inductive research methods and algorithmic HRM leads to challenges, most notably ML opacity. Consequently, stakeholders may not act optimally, based on the ML predictions and insights proposed by algorithms, or accept the results (Meijerink et al. 2021, p. 2550). Similarly, ML-based inductive research offers a useful methodology only if the ML models are sufficiently transparent to extract insights.

2.6.1 Predictive Performance vs. Transparency Trade-Off

Accordingly, we come back to RQ1. Our results empirically demonstrate a significant trade-off between predictive performance and transparency in real-world employee turnover prediction data that is not found in artificially simulated datasets used in similar studies (Choudhury et al. 2021; Chowdhury et al. 2022). This suggests that artificially generated datasets may not holistically capture the sophistication of the various causes of employee turnover so that transparency-by-design approaches may be sufficient. Our results suggest that real-world HR prediction tasks like employee turnover prediction face a level of complexity that cannot be adequately solved by simpler transparency-by-design algorithms. The relationships between predictors and employee turnover elude linear relationships, making nonlinearities and heterogeneous interactions essential for accurately predicting the multifaceted causes of turnover (Putka et al. 2018, p. 721). Thus, the transparency-by-design approach may not be applicable in some real-world HR applications, leaving complex ML models. This supports recent theoretical research citing that opacity is a key characteristic and default of ML due to system-based opacity, caused by ML algorithm complexity and the scale required for meaningful application (Burrell 2016; Kellogg et al. 2020; Langer and König 2023).

2.6.2 Extracting Multifaceted Relationships

To understand the rationale behind complex ML model predictions, such as the Random Forest model, we propose three post-hoc explanatory methods that support the extraction of multifaceted insights on predictions. The three proposed XAI methods support translating the patterns used by opaque ML algorithms into human-understandable results. These patterns can also be multifaceted, such as nonlinearity and heterogeneous feature interactions. To accomplish this, all three proposed methods account for the extent to which predictors influence employee turnover prediction. However, each method takes a distinct mathematical approach and focuses on different aspects of information (e.g. local vs. global). ALE helps identify nonlinear and heterogeneous causes of turnover among employee subgroups, including otherwise unnoticed insights; for example, in this empirical setting for turnover, (1) a U-shaped relationship with commuting distance (Figure 7), (2) interactions between the predictors age and gender (Figure 7), specifics of relevant predictors in diverse subgroups (Figure 8). SHAP highlights the specifics at the local level, allowing for the analysis of individuals. Such inductive findings can serve as the basis for theory development or complement deductive methods for deriving prescriptive and generalisable implications (Yuan et al. 2021, p. 3).

2.6.3 Criticism of Post-Hoc Explanations

Finally, we discuss limitations of post-hoc explanations and their consequences for appropriate use. Other studies use post-hoc explanatory methods to demonstrate their capabilities for deeper investigation, although transparency-by-design approaches using linear logistic regression are sufficient (e.g. Choudhury et al. 2021; Chowdhury et al. 2022). In these cases, post-hoc explanatory methods (especially on local level) have been seriously criticised for high-stakes decision-making like HRM by technical experts, due to several risks resulting from the simplistic inaccuracies, and instead call for transparency-by-design approaches (Rudin 2019). Similarly, healthcare researchers refer to post-hoc explanations as a '*false hope*' because stakeholders may misinterpret the ML model's capabilities, mainly due to possible explanation inaccuracy (Ghassemi et al. 2021, 745) resulting from approximating the ML model to the real-world as well as the post-hoc explanatory method to the ML model. Due to this heuristic nature, the rationale behind predictions must be carefully questioned (Cheng and Hackett 2021). As a result of the resulting unreliability and superficial character of post-hoc explanation, Ghassemi et al. (2021) advise to not use post-hoc explanatory methods to access possible biases towards certain populations, to reassure for correct individual decisions, to increase trust or to justify acceptance of the ML model. They therefore call for using global explanatory methods only to understand how the ML model behaves at a global level and emphasise that they should be combined with rigorous prediction validation processes for different populations (Ghassemi et al. 2021, 745). Legal studies follow a similar line of reasoning, based on technical limitations such as results instability, stating that post-hoc explanatory methods cannot establish abstinence of discrimination caused by various biases embedded in ML models (Vale et al. 2022).

2.6.4 Justification for Post-Hoc Explanatory Methods

Concluding, in response to RQ2, post-hoc explanatory methods help examine the rationality of complex ML models to understand why they make incorrect predictions or reveal possible adverse impacts at the global level. However, given their limitations, they should be used with caution to justify individual-level personnel decisions. Post-hoc explanations should not be used as the only truth when formulating and justifying decisions where the stakes are high, but they are a helpful addition. Together, we argue for a nuanced perspective on the justified use of post-hoc explanations methods in circumstances where the transparency-by-design approach fails and managers are aware of its limitations. In these cases, despite the criticisms, post-hoc explanatory methods are the most feasible way to mitigate the trade-off between predictive performance and transparency. Furthermore, as they provide only an approximation of complex ML models, they may serve as a source of information but cannot be regarded as the definitive ground truth. Thus, the validity of ML predictions and post-hoc explanations must be critically questioned following existing evidence, theory and domain knowledge to ensure causality (Erel et al. 2021, p. 3245). As an illustration, the plausibility of the relationships presented in the

ALE plot (Figure 7) is supported by employee turnover studies indicating similar results. Similarly, the consistency of patterns discovered in relation to expertise can be evaluated against other organisation-specific information, such as survey-based data and exit interviews.

2.6.5 Implications for Research

We contribute to the ML in HRM literature in three ways. First, we empirically demonstrate the trade-off between predictive performance and transparency in real-world data. In this context, our research documents that ML opacity may be unavoidable in some real-world HR prediction tasks, as the underlying algorithms must have considerable complexity to achieve adequate performance. Therefore, transparency-by-design approaches are not always applicable, as predictive performance does not sufficiently solve the prediction task. Second, we provide a nuanced perspective on the justified use of post-hoc explanatory methods, i.e. to mitigate the trade-off between predictive performance and transparency when it occurs in the HRM application – and transparency-by-design approaches are not sufficient. Third, we demonstrate the complementary use of local and global post-hoc explanatory methods to understand nonlinearities and heterogeneity in complex ML models.

Together, these three contributions have a methodological implication and can serve as a guideline when applying the ML-based inductive research method. Based on the extent of the trade-off with different algorithms during the experimentation phase, researchers may decide to adopt a transparency-by-design approach if it is suitable to solve the prediction task adequately. Alternatively, the three proposed post-hoc explanatory methods can help extract additional nonlinear and heterogenous insights. In contrast to existing studies that use a single post-hoc explanatory method (Choudhury et al. 2021; Chowdhury et al. 2022), we provide a broader picture of available technical solutions and demonstrate the joint use of local and global post-hoc methods in a complementary manner. However, for both methods, reliance on the human ability to make ethical and moral judgments, in order to critically question and rigorously validate the results of ML algorithms should be emphasised in both research and practice. To advance HRM knowledge, we therefore advocate a hybrid methodological approach, combining ML-based inductive, exploratory findings with validation by existing evidence and theories or by subsequent deductive, confirmatory studies. Accordingly, HRM research benefits from ML-based methods by (1) testing and refining theories and (2) expanding the explanatory range of theories

(Leavitt et al. 2021). Additionally, we also make a secondary contribution to the HRM literature on employee turnover by suggesting that examining nonlinearities and heterogeneity is important in fully capturing the intricacies of the various pathways resulting in turnover.

2.6.6 Implications for Practice

For HRM practitioners, the well-known promises of objective and accurate ML-based decisions are only valid if models are not kept opaque. Instead, causality behind predictions must be verified through a hybrid human-ML development process before they can be used for individual decision-making (van den Broek et al. 2021). In this context, applying knowledge of the revealed trade-off between predictive performance and transparency guides a more informed algorithm selection in ML development. As technically-oriented functions such as data scientists may lack an understanding of opaque ML models' impact on HRM applications (Charlwood and Guenole 2022, p. 2), we suggest that organisations invest in educating HR staff about the consequences of ML complexity. In evaluating the potential impact on individual employees, HR managers can then weigh the predictive power or transparency of ML models on a continuum.

Educating HR decision-makers about the capabilities and limitations of post-hoc explanatory methods is also advisable; otherwise, they may not be able to "*use their tacit experience and social intelligence (based on intuitive thinking) to determine the accuracy of the model*" when using complex ML models (Chowdhury et al. 2022, p. 20). Properly applied complex ML algorithms combined with post-hoc explanatory methods can mitigate the trade-off between predictive performance and transparency. This contributes to realise ML's potential to study and predict voluntary employee turnover and understand its multifaceted causes. The ALE plots' global explanations identify possible organisation-wide improvements or new retention strategies targeting influencing predictors, e.g. we find that *commuting distance* is an important turnover determinant, implying that a higher home-office ratio might be an effective countermeasure. ML predictions can be used in conjunction with nonlinear insights from ALE or individual-level explanations from SHAP to identify heterogeneous retention strategies for departments and demographic subgroups, or to personalise for employees, which would not be possible with linear models (Chowdhury et al. 2022, p. 15).

Ultimately, and particularly for public sector organisations, post-hoc explanatory methods might be a door-opener for ML-based methods. Public organisations must be highly transparent in their decision-making due to their high societal responsibility. Consequently, many public organisations have not yet started integrating ML-based solutions into their operations, one central reason for which is legal uncertainty related to the lack of transparency of such approaches. This was also one main reason for the examined federal agency in testing post-hoc explanatory methods and might be of similar interest for many other public sector executives seeking solutions in integrating reliable and trustworthy algorithmic HRM in their day-to-day business (Chowdhury et al. 2022, p. 24).

2.6.7 Limitations and Directions for Future Research

Our first limitation is that inductive HRIS-oriented research does not provide deep insights in the same way that studies based on surveys do. Thus, pure data from HRIS and an inductive perspective should be used to complement existing theory-oriented research methods, e.g. for characterising risk groups or sub-organisational specifics (Rombaut and Guerry 2018, p. 97). In future research, the framework presented herein with post-hoc explanatory methods can be applied not only to data available in HRIS, but also to psychological studies' survey-based data. Thus, the inductive research method can serve as a complementary framework to study multifaceted relationships between multiple predictors. Unlike deductive research, comprehensive theory is not required to specify relationships in advance, thereby helping identify nonlinear and heterogenous relationships also for psychological constructs that predictors in studies based on linear models might miss (Putka et al. 2018, p. 690). Accordingly, we endorse the management literature (Leavitt et al. 2021; Valizade et al. 2024) by recommending ML as a powerful tool for quantitative research. Our results herein support the prioritisation of algorithms in terms of '*transparency-by-design*' or more complex algorithms in coordination with post-hoc explanatory methods.

Second, it is important to note that advantages and disadvantages of the three applied post-hoc explanatory methods may not be generalisable to options beyond the scope of this work. Further, HRM research should be aware of the rapid development of ML algorithms and XAI, as computer scientists attempt to resolve the trade-off by developing new transparency-by-design algorithms to increase their predictive performance, as well as new post-hoc explanatory methods (e.g. Arrieta et al. 2020).

Third, we focus on one federal agency in an in-depth examination, which means we forfeit some generalisability (Yin 2013, p. 325). We encourage future research to investigate implications of the trade-off in diverse other (multi-)national settings and in other ML-based prediction tasks in HR besides employee turnover prediction, such as employee selection, training and management.

2.7 Conclusion

This study discloses the trade-off between predictive performance and transparency in ML empirically demonstrated in a real-world HRM application, meaning that complex – and therefore opaque – algorithms have significantly better predictive performance. For sophisticated prediction tasks such as employee turnover, the underlying algorithms must have considerable complexity and therefore cannot be adequately solved by simpler transparency-by-design ML algorithms. However, by applying three post-hoc explanatory methods to successful but opaque ML models, insights are gained that include nonlinear and heterogeneous causes of employee turnover. We argue that post-hoc explanatory methods help mitigate the trade-off if they are used properly according to their limitations and are not blindly trusted, which is why we emphasise a nuanced perspective to their justified use. We hope that this paper motivates further research regarding ML transparency as a necessity to pave the way for an ethically and a legally compliant ML-augmented decision-making process that benefits the organisation and – most importantly – all employees.

2.8 List of References

Apley, Daniel W.; Zhu, Jingyu (2020): Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models. In: Journal of the Royal Statistical Society: Series B (Statistical Methodology) 82 (4), pp. 1059–1086. DOI: 10.1111/rssb.12377.

Arrieta, Alejandro B.; Díaz-Rodríguez, Natalia; Del Ser, Javier; Bennetot, Adrien; Tabik, Siham; Barbado, Alberto; Garcia, Salvador; Gil-Lopez, Sergio; Molina, Daniel; Benjamins, Richard; Chatila, Raja; Herrera, Francisco (2020): Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. In: Information Fusion 58, pp. 82–115. DOI: 10.1016/j.inffus.2019.12.012.

van den Broek, Elmira; Sergeeva, Anastasia; Huysman Vrije, Marleen (2021): When the Machine Meets the Expert: An Ethnography of Developing AI for Hiring. In: MIS Quarterly 45 (3), pp. 1557–1580. DOI: 10.25300/MISQ/2021/16559.

Burrell, Jenna (2016): How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms. In: Big Data & Society 3 (1). DOI: 10.1177/2053951715622512.

Charlwood, Andy; Guenole, Nigel (2022): Can HR Adapt to the Paradoxes of Artificial Intelligence? In: Human Resource Management Journal 32 (4), pp. 729–742. DOI: 10.1111/1748-8583.12433.

Cheng, Maggie M.; Hackett, Rick D. (2021): A Critical Review of Algorithms in HRM: Definition, Theory, and Practice. In: Human Resource Management Review 31 (1), p. 100698. DOI: 10.1016/j.hrmr.2019.100698.

Choudhury, Prithwiraj; Allen, Ryan T.; Endres, Michael G. (2021): Machine Learning for Pattern Discovery in Management Research. In: Strategic Management Journal 42 (1), pp. 30–57. DOI: 10.1002/smj.3215.

Chowdhury, Soumyadeb; Joel-Edgar, Sian; Dey, Prasanta Kumar; Bhattacharya, Sudeshna; Kharlamov, Alexander (2022): Embedding Transparency in Artificial Intelligence Machine Learning Models: Managerial Implications on Predicting and Explaining Employee Turnover. In: The International Journal of Human Resource Management 34 (14), pp. 2732–2764. DOI: 10.1080/09585192.2022.2066981.

Cohen, Jacob (1960): A Coefficient of Agreement for Nominal Scales. In: Educational and Psychological Measurement 20 (1), pp. 37–46. DOI: 10.1177/001316446002000104.

Edwards, Martin R.; Charlwood, Andy; Guenole, Nigel; Marler, Janet (2022): HR Analytics: An Emerging Field Finding Its Place in the World alongside Simmering Ethical Challenges. In: Human Resource Management Journal 34 (2), pp. 326-336. DOI: 10.1111/1748-8583.12435.

Erel, Isil; Stern, Léa H.; Tan, Chenhao; Weisbach, Michael S. (2021): Selecting Directors Using Machine Learning. In: The Review of Financial Studies 34 (7), pp. 3226–3264. DOI: 10.1093/rfs/hhab050.

Gal, Uri; Jensen, Tina Blegind; Stein, Mari-Klara (2020): Breaking the Vicious Cycle of Algorithmic Management: A Virtue Ethics Approach to People Analytics. In: Information and Organization 30 (2), p. 100301. DOI: 10.1016/j.infoandorg.2020.100301.

Ghassemi, Marzyeh; Oakden-Rayner, Luke; Beam, Andrew L. (2021): The False Hope of Current Approaches to Explainable Artificial Intelligence in Health Care. In: Lancet Digital Health 3 (11), pp. 745–750. DOI: 10.1016/S2589-7500(21)00208-9.

Gray, Alastair M.; Phillips, V. L. (1994): Turnover, Age and Length of Service: A Com-Parison of Nurses and Other Staff in the National Health Service. In: Journal of Advanced Nursing 19 (4), pp. 819–827. DOI: 10.1111/j.1365-2648.1994.tb01155.x.

Grissom, Jason A.; Viano, Samantha L.; Selin, Jennifer L. (2016): Understanding Employee Turnover in the Public Sector: Insights from Research on Teacher Mobility. In: Public Administration Review 76 (2), pp. 241–251. DOI: 10.1111/puar.12435.

Holtom, Brooks C.; Mitchell, Terence R.; Lee, Thomas W.; Eberly, Marion B. (2008): 5 Turnover and Retention Research: A Glance at the Past, a Closer Review of the Present, and a Venture into the Future. In: The Academy of Management Annals 2 (1), pp. 231–274. DOI: 10.1080/19416520802211552.

Kellogg, Katherine C.; Valentine, Melissa A.; Christin, Angéle (2020): Algorithms at Work: The New Contested Terrain of Control. In: Academy of Management Annals 14 (1), pp. 366–410. DOI: 10.5465/annals.2018.0174.

King, Kylie Goodell (2016): Data Analytics in Human Resources. In: Human Resource Development Review 15 (4), pp. 487–495. DOI: 10.1177/1534484316675818.

Kuhn, Max (2019): Building Predictive Models in R Using the Caret Package. Available online at: https://topepo.github.io/caret/index.html, updated on: March 27, 2019 (retrieved on July 7, 2025).

Landis, J. Richard; Koch, Gary G. (1977): An Application of Hierarchical Kappa-Type Statistics in the Assessment of Majority Agreement among Multiple Observers. In: Biometrics 33 (2), p. 363. DOI: 10.2307/2529786.

Langer, Markus; König, Cornelius J. (2023): Introducing a Multi-Stakeholder Perspective on Opacity, Transparency and Strategies to Reduce Opacity in Algorithm-Based Human Resource Management. In: Human Resource Management Review 33 (1), p. 100881. DOI: 10.1016/j.hrmr.2021.100881.

Leavitt, Keith; Schabram, Kira; Hariharan, Prashanth; Barnes, Christopher M. (2021): Ghost in the Machine: On Organizational Theory in the Age of Machine Learning. In: Academy of Management Review 46 (4), pp. 750–777. DOI: 10.5465/amr.2019.0247.

Lin, Li; Bai, Yuntao; Mo, Changwei; Liu, Dong; Li, Xiyuan (2021): Does Pay Raise Decrease Temporary Agency Workers' Voluntary Turnover over Time in China? Understanding the Moderating Role of Demographics. In: The International Journal of Human Resource Management 32 (7), pp. 1537–1565. DOI: 10.1080/09585192.2018.1539861.

Lundberg, Scott; Lee, Su-In (2017): A Unified Approach to Interpreting Model Predictions. In: Proceedings of the 31st International Conference on Neural Information Processing System. Available online at: http://arxiv.org/pdf/1705.07874v2 (retrieved on July 7, 2025).

Meijerink, Jeroen; Boons, Mark; Keegan, Anne; Marler, Janet (2021): Algorithmic Human Resource Management: Synthesizing Developments and Cross-Disciplinary Insights on Digital HRM. In: The International Journal of Human Resource Management 32 (12), pp. 2545–2562. DOI: 10.1080/09585192.2021.1925326.

Molnar, Christoph (2022): Interpretable Machine Learning – A Guide for Making Black Box Models Interpretable. 2. Edition. Morisville, North Carolina: Lulu.

Molnar, Christoph; Casalicchio, Giuseppe; Bischl, Bernd (2018): Iml: An R Package for Interpretable Machine Learning. In: Journal of Open Source Software 3 (26), p. 786. DOI: 10.21105/joss.00786.

Putka, Dan J.; Beatty, Adam S.; Reeder, Matthew C. (2018): Modern Prediction Methods: New Perspectives on a Common Problem. In: Organizational Research Methods 21 (3), pp. 689–732. DOI: 10.1177/1094428117697041.

Rombaut, Evy; Guerry, Marie-Anne (2018): Predicting Voluntary Turnover through Human Resources Database Analysis. In: Management Research Review 41 (1), pp. 96–112. DOI: 10.1108/MRR-04-2017-0098.

Rombaut, Evy; Guerry, Marie-Anne (2021): Determinants of Voluntary Turnover: A Data-Driven Analysis for Blue and White Collar Workers. In: Work 69 (3), pp. 1083–1101. DOI: 10.3233/WOR-213538.

Rubenstein, Alex L.; Eberly, Marion B.; Lee, Thomas W.; Mitchell, Terence R. (2018): Surveying the Forest: A Meta-Analysis, Moderator Investigation, and Future-Oriented Discussion of the Antecedents of Voluntary Employee Turnover. In: Personnel Psychology 71 (1), pp. 23–65. DOI: 10.1111/peps.12226.

Rudin, Cynthia (2019): Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead. In: Nature Machine Intelligence 1 (5), pp. 206–215. DOI: 10.1038/s42256-019-0048-x.

Russell, Craig J.; Sell, Mary V. (2012): A Closer Look at Decisions to Quit. In: Organizational Behavior and Human Decision Processes 117 (1), pp. 125–137. DOI: 10.1016/j.obhdp.2011.09.002.

Shwartz-Ziv, Ravid; Armon, Amitai (2022): Tabular Data: Deep Learning Is Not All You Need. In: Information Fusion 81, pp. 84–90. DOI: 10.1016/j.inffus.2021.11.011.

Somers, Mark J.; Birnbaum, Dee; Casal, Jose (2021): Supervisor Support, Control over Work Methods and Employee Well-Being: New Insights into Nonlinearity from Artificial Neural Networks. In: International Journal of Human Resource Management 32 (7), pp. 1620–1642. DOI: 10.1080/09585192.2018.1540442.

Speer, Andrew B. (2021): Empirical Attrition Modelling and Discrimination: Balancing Validity and Group Differences. In: Human Resource Management Journal. DOI: 10.1111/1748-8583.12355.

Vale, Daniel; El-Sharif, Ali; Ali, Muhammed (2022): Explainable Artificial Intelligence (XAI) Post-Hoc Explainability Methods: Risks and Limitations in Non-Discrimination Law. In: AI and Ethics 2 (4), pp. 815–826. DOI: 10.1007/s43681-022-00142-y.

Valizade, Danat; Schulz, Felix; Nicoara, Cezara (2024): Towards a Paradigm Shift: How Can Machine Learning Extend the Boundaries of Quantitative Management Scholarship? In: British Journal of Management 35 (1), pp. 99–114. DOI: 10.1111/1467-8551.12678.

Yakusheva, Olga; Bang, James T.; Hughes, Ronda G.; Bobay, Kathleen L.; Costa, Linda; Weiss, Marianne E. (2022): Nonlinear Association of Nurse Staffing and Readmissions Uncovered in Machine Learning Analysis. In: Health Services Research 57 (2), pp. 311–321. DOI: 10.1111/1475-6773.13695.

Yin, Robert K. (2013): Validity and Generalization in Future Case Study Evaluations. In: Evaluation 19 (3), pp. 321–332. DOI: 10.1177/1356389013497081.

Yuan, Shuai; Kroon, Brigitte; Kramer, Astrid (2021): Building Prediction Models with Grouped Data: A Case Study on the Prediction of Turnover Intention. In: Human Resource Management Journal 34 (1), pp. 20–38. DOI: 10.1111/1748-8583.12396.

3 Exploring the Individual Adoption of Human Resource Analytics: Behavioural Beliefs and the Role of Machine Learning Characteristics

3.1 Publication Details

Abstract:

The technological capabilities of Human Resource Analytics (HRA), enhanced by recent innovations in Machine Learning (ML), offer exciting opportunities. However, organisations often fail to realise these potentials because of a limited understanding of why individuals choose to adopt or disregard respective tools. Prior research on innovation adoption offers preliminary insights but fails to aggregate the determinants of individual adoption into actionable suggestions for decisions in the ML adoption process. Our study applies *Focused Interviews* to examine non-ML experts' reasoning for using a specific tool tailored to a public sector organisation, which corresponds to the usual end-user perspective of ML-based HRA adoption. By drawing from the HRA adoption framework, provided by Vargas et al. (2018), we contribute to the literature by identifying relevant beliefs and experiences influencing one's intention to adopt ML-based HRA and by qualitatively linking these beliefs to ML characteristics such as transparency, automation and fairness. For practitioners, we provide actionable guidance emphasising the need to ensure fairness proactively, as interviewees do not consider this aspect when deciding to adopt ML-based HRA.

Co-Authors: Christian Ertel, Ansgar Heidemann

Keywords: Human Resource Analytics, Machine Learning Adoption, Explainable Artificial Intelligence, Theory of Planned Behaviour, Employee Turnover Prediction

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3.2 Introduction

The diffusion of analytics into Human Resources Management (HRM) processes, including talent management, performance evaluation and workforce planning, presents a promising opportunity. Human Resources Analytics (HRA), as it is referred to in this context, is classified as diffusing innovation and describes "*a practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to Human Resources (HR) processes, human capital, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making*" (Marler and Boudreau 2017, p. 15). Modern-day technological advances help HR professionals asserting their value when defending against possible displacement by finance or data science departments (Angrave et al. 2016), and they provide support for a wide range of different HR functions (Prikshat et al. 2023a). In recruitment, for example, HRA can be used to streamline processes and achieve greater speed and efficiency (Hunkenschroer and Luetge 2022), whilst in HR development, it helps to identify the link between employee engagement and performance metrics – and thus positively influences them (Davenport et al. 2010). Although traditional HRA encompasses several statistical approaches and methodologies, Machine Learning (ML), such as deep-learning algorithms, and Artificial Intelligence, is expected to drive the greatest change in HRM practice. For example, online work platforms such as Uber, Upwork and Deliveroo automate extensive core business processes, ranging from HRM decision-making to execution in the form of selection, compensation and task assignment – all of which is done through ML (Meijerink et al. 2021). In addition, ML-based HRA tools for predicting voluntary employee turnover allow companies to derive retention strategies that not only reduce costly replacements in the short term, but also retain expertise within the organisation, thereby securing a competitive advantage (Chowdhury et al. 2022).

Prior research identifies individual resistance to ML-based HRA which could hinder its success in corporate practice. In contrast to other HRA technologies, sophisticated ML algorithms, for instance, have the disadvantage of being too complex to interpret easily, which subsequently leads to opacity (Kellogg et al. 2020; Langer and König 2021). As more data and multifaceted algorithms become available, a computer learns more complex patterns and "*consequently builds its own representation of a classification decision, [which it does] without regard for human comprehension*" (Burrell 2016, p. 10). Therefore, algorithms exceed human abilities to understand the system and can generate severe trust issues (Arrieta et al. 2020). Furthermore, prior research observes attempts to manipulate and exploit these advanced ML-based systems, known as *Algoactivism* (Kellogg et al. 2020; Meijerink and Bondarouk 2023), and a more general aversion to advanced algorithms, called *Algorithm Aversion* (Mahmud et al. 2022). Consequently, the successful leverage of the described potential of ML-based HRA critically depends on the ability to convince the individuals of an organisation to use these systems (Di Vaio et al. 2022).

However, as most academic HR literature aims to understand the factors determining the adoption of HRA on an organisation-wide level (e.g. Margherita 2022), and irrespective of the specific tool (e.g. Vargas et al. 2018), there is very little knowledge on the successful individual adoption of HRA – and especially ML-based HRA. Coming from the apparent need for a better understanding of the individual adoption process for ML-based HRA, as well as the ambiguous effect of ML characteristics, we ask the following two research questions:

> **RQ1**: What beliefs and experiences influence the individual's intention to adopt ML-based HRA?
>
> **RQ2**: How do the characteristics of ML engender these behavioural beliefs?

To answer these research questions, we examine the individual opinions and thoughts of employees of a public sector organisation about a specific ML-based HRA tool for predicting voluntary turnover, the implementation of which the organisation is currently evaluating. Drawing from the *Focused Interviews* method provided by Merton and Kendall (1946), we discuss the performance of the predictive HRA tool, as well as several explanatory figures, with employees in interviews and analyse their personal perspectives, experiences and spontaneous reactions to these different approaches. Following Vargas et al. (2018), we then interpret our empirical results with the help of a conceptual framework derived from the *Theory of Planned Behaviour* (TPB) by Ajzen (1991). On the one hand, our results show that the perceived (self-)efficacy of interviewees also highly depends on the design of the HRA tool and the entered dataset, in addition to perceived skills and competencies. On the other hand, the attitude of the interviewed employees is not only formed by their personal enjoyment or concerns in terms of working with the tool, but also by the way in which they perceive it assists them in their daily work. We additionally identify that several ML characteristics (perceived self-learning capabilities, degree of automation, transparency and trialability) influence behavioural beliefs and in turn effect the adoption of the tool in HRM processes.

Our study makes three main contributions to the literature. First, it contributes to the ongoing debate about the relevant factors driving the decision to adopt HRA (Coolen et al. 2023). By examining this decision from an individual instead of an organisation-wide perspective, we provide deeper insights into the different behavioural beliefs determining the decision to adopt ML-based HRA. Based on our findings, we propose several ML-related extensions and adjustments to the more general adoption framework of Vargas et al. (2018). Second, our study contributes to the current literature on ML design approaches and their effect on HRA adoption (Marler and Boudreau 2017; Langer and König 2021; Haque et al. 2023), and third, it contributes to research on ML transparency, suggesting that appropriate visualisation influences end-user adoption (Haque et al. 2023). However, in contrast with Haque et al. (2023), our results demonstrate a lack of ethical reflection, as fairness plays no role in individual decisions to adopt ML-based HRA, albeit protected group differences were made apparent in the interviews.

The paper is organised as follows. The second section reviews the literature on the (individual) adoption of HRA, highlights the related limitations and derives the conceptual framework of our study. The third section summarises the research method, empirical environment as well as the research object and data analysis process. The fourth section presents the results. A refined model at the end of this section summarises the factors that influence individual intentions to adopt ML-based HRA and the impact of ML characteristics. Finally, in the fifth section, the results are discussed and propositions made before a conclusion is drawn.

3.3 Related Research and Theoretical Framework

In the following section, a conceptual framework for the present study is derived by summarising and discussing the state of knowledge on the (individual) adoption of HRA.

3.3.1 Prior Research Regarding the Adoption of HR Analytics

The factors that drive or hinder the adoption of HRA have been almost exclusively explored from an organisation-wide perspective (e.g. Margherita 2022; Böhmer and Schinnenburg 2023; Coolen et al. 2023). Prior research draws from the TOE framework (e.g. Pumplun et al. 2019; Chatterjee et al. 2021; Neumann et al. 2022), with the underlying idea that the adoption of HRA from an organisation-wide perspective is mainly driven by technological, organisational and environmental contexts. Technological contexts include, for example, the existing IT infrastructure of an organisation (Neumann et al. 2022), while the environmental contexts can be, for example, competitive pressure or customer readiness (Neumann et al. 2022). The organisational context includes cultural aspects (such as the culture of innovation or change management) as well as resources (e.g. budgets or human capital) (Neumann et al. 2022). Prior research concludes that the employees themselves – aligned with their skills and knowledge – play a major role in the adoption of HRA in corporations (Di Vaio et al. 2022; Coolen et al. 2023). Furthermore, work ethics (Basu et al. 2023) or supervisor support (Prikshat et al. 2023b) have been identified as additional major drivers for organisation-wide adoption.

To the best of the authors' knowledge, only Vargas et al. (2018) have examined the individual adoption of HRA and proposed a comprehensive framework in this regard. Drawing from the *Theory of Planned Behaviour* by Ajzen (1991) and the *Innovation Diffusion Theory* posited by Rogers (2003), the authors explain the actual level of adoption of HRA through an individual's perceived self-efficacy, attitude and social influence regarding its use as well as trialability. Self-efficacy represents an individual's beliefs about their abilities to reach a behavioural goal (Bandura 1977), which translates to their evaluation of the technological and quantitative skills they deem necessary to adopt HRA. One's attitude towards a specific behaviour is derived from the expected consequences of this behaviour (Fishbein and Ajzen 2010). As the perceived consequences of using HRA partly depend on an individual's self-efficacy regarding the use of HRA, the latter will influence their attitude, among several other beliefs for the given context. Social influence represents the perceived norms in favour of or against HRA, and trialability encompasses beliefs about the degree to which HRA can be tested before adoption. Vargas et al. (2018) distinguish the three different decision-making steps of knowledge-gathering, persuasion and decision, whereby perceived self-efficacy is formed during the knowledge-gathering step, and attitude, social influence and trialability are derived during the persuasion step. The conducted survey empirically supports the proposed causal relationships as well as the effect of technology self-efficacy.

3.3.2 Limitations of the HR Analytics Conceptual Framework

While the derived conceptual framework provided by Vargas et al. (2018) extends the fundamental understanding of individual HRA adoption, it does have some limitations. First, it only includes trialability as a potential technological factor to distinguish between different HRA technologies. The proliferation of ML questions the reality, as the framework does not distinguish between the different characteristics of the HRA tool. Furthermore, as HRA includes many different algorithms, systems and methods (Meijerink et al. 2021), and prior research in Information Systems finds significant effects of an IT systems's design on its subsequent use (Haque et al. 2023), there is clearly the need to further characterise and differentiate the proposed model from this perspective. Especially in the context of ML, research has emerged in the HR (Langer and König 2021), Management (Glikson and Woolley 2020) and Information Systems (Arrieta et al. 2020) literature arguing that transparency must be another fundamental determinant of individual ML adoption. In contrast to traditional statistical methods in HRA, transparency is not always present in ML, because (a) predictors are not understandable, (b) relationships between predictors and predictions are hidden and (c) no explanation for a specific prediction is given (Burrell 2016; Arrieta et al. 2020; Langer and König 2021). This is problematic, because a prediction without clear explanations, or at least justification for the rationale behind the prediction, can lead to trust issues (Glikson and Woolley 2020; Langer and König 2021). Park et al. (2021), for instance, illustrate that only with sufficient transparency can various user burdens (emotional, mental, biases, etc.) be overcome during ML adoption. Transparency is also closely related to another fundamental determinant of HRA adoption, namely fairness (e.g. no discrimination against minorities), which can only be tested when professionals use their expertise and experience to determine the level of fairness of individual ML predictions through intuitive thinking (Chowdhury et al. 2022). To achieve sufficient ML transparency, *Explainable Artificial Intelligence* (XAI) offers a rapidly evolving interdisciplinary research area with multiple technical solutions (Arrieta et al. 2020). Finally, the ability to automate decisions fully is an ML characteristic that represents a major shift for traditional HRA technologies (Meijerink et al. 2021). When algorithms are used for automated scenarios, they must also be accountable for the decisions they make (Busuioc 2021). In summary, and in line with Lee and Cha (2023), we suggest that transparency, fairness and accountability (in terms of automated use) determine the adoption of ML-based HRA. Besides technical ML characteristics, decisions made during roll-out also affect the adoption of ML. In this regard, some studies have found that the ability to try (= trialability) has a positive impact on adoption (Omrani et al. 2022). However, research is still inconclusive in terms of exactly how these ML characteristics influence an individual's adoption of HRA.

Second, the notion of self-efficacy and attitude in the proposed framework of Vargas et al. (2018) is relatively narrow, and it might exclude potentially relevant beliefs. Compared to assumed self-efficacy, the *Perceived Behavioural Control* (PBC) factor from the original TPB is a wider concept that includes beliefs about factors beyond one's individual control (Ajzen 1991). It can be defined as the perceived ease or difficulty of performing a behaviour (Ajzen 2002). For instance, the individual adoption of an HRA tool likely depends on the tool's suitability for a task and not only on one's perceived skills to use it. Furthermore, Vargas et al. (2018) examine self-efficacy regarding technology and mathematics in general, which are sufficient to estimate the average intention to adopt HRA but fall short when comparing the adoption of different HRA systems. However, the TPB is built upon the principle of compatibility, which states that the underlying factors must always refer to the underlying behaviour (Fishbein and Ajzen 2010). For the given context, one would therefore expect a notion of self-efficacy that is more directly connected to the individual adoption of a specific HRA tool or system. Furthermore, the attitude of a survey participant is derived from four beliefs solely centred around the personal enjoyment of using HRA (Vargas et al. 2018). This notion contrasts with the *Technology Acceptance Model* that connects the attitude towards a technology to the beliefs about the perceived usefulness and perceived ease of use of a technology (Davis 1989) and the *Unified Theory of Acceptance and Use of Technology* that connects the respective attitude to a performance and effort expectancy (Ajzen 2002; Venkatesh et al. 2003).

3.3.3 Underlying Conceptual Framework Theory

Due to the limitations of the conceptual framework of Vargas et al. (2018) described herein, we aim to scrutinise the framework and extend it to ML-based HRA tools. Our further analyses are based on the assumptions described above, which are founded on the current state of knowledge. We also distinguish between the process steps of knowledge, persuasion and decision (Rogers 2003) in an ML-based HRA tool's adoption process. In the knowledge step, personal beliefs are evaluated regarding the ability to utilise an ML-based HRA tool for a given task and form an expectation about the PBC. In the persuasion phase, personal beliefs are evaluated regarding the consequences of using the provided HRA tool and form a tool and task-specific attitude. In addition, personal beliefs are evaluated regarding the opinions of others regarding the use of the provided HRA tool and form an expectation about the relevant social norm (corporate or national culture). In the decision step, personal beliefs are evaluated regarding the PBC, attitude as well as perceived norm and help decide whether to adopt the provided HRA tool. Furthermore, we expect PBC and attitudes to be influenced by the technical characteristics of the provided

ML-based HRA tool, in which case we distinguish between the known characteristics of trialability, transparency, degree of automation and fairness and potential unknown characteristics.

3.4 Research Approach

3.4.1 Method

To fill the derived conceptual framework for individual adoption with salient beliefs, it is necessary to dive deep into the line of reasoning employed by end-users. We aim to explore these beliefs by applying the '*Focused Ethnographic Interview*' methodology proposed by Merton and Kendall (1946). We opted for a qualitative research approach because it can provide new insights into individual adoption in an explanatory manner. In addition, the open-ended nature of the interview questions allows for the collection of a wide range of information, including personal perspectives and experiences. The interview procedure was semi-structured around several pieces of information and nudges, used as potential triggers for spontaneous reactions. During the interview, detailed discussions were held on hypothetical but realistic implementation scenarios for the specific HRA tool. Particular attention was paid to employees' understanding of the presented tool, their ideas about its future use in HRM processes and their perceptions of the risks and benefits of using it in various HR applications throughout the organisation. In addition, the interviews provided information about the overall intentions of the interviewees as well as any changes in their intention to adopt the HRA tool when providing various information and explanations. This approach follows the interpretive tradition of explorative methods, in that it seeks a deep understanding of human experience rather than rigid explanations of cause and effect – as in positivist epistemology (Einola and Khoreva 2023).

3.4.2 Empirical Environment

This study examines a German federal agency from the social insurance industry with about 20,000 employees in the period between 2022 and 2023. The in-depth public sector study approach provides a context in which high legal requirements for the individual adoption of HRA can be investigated and commercial secrecy is not a concern (Desouza et al. 2020; Busuioc 2021). While the organisation frequently uses descriptive analytics based on advanced dashboarding tools, as well as sporadic diagnostic regression-based analytics, this project is the first to incorporate complex ML models to implement predictive analytics use cases within HR.

Our main objective in selecting the interview population was to obtain a diverse sample of HRA users in terms of personal characteristics (age and gender), seniority and statistical background in order to represent the diverse workforce of the organisation as well as the different usage objectives in the different personas. Table 10 provides an overview of the 12 interviewees. Team leaders supervising one to 21 employees, and heads of departments with 21 to 50 employees, from HR and operational departments, are the main users of the HRA tool. Half of the employees interviewed would work with the HRA tool in the near future, and half of those interviewed were potential recipients for further applications. Each interview lasted between 58 and 98 minutes.

Table 10: Interview population of future HR Analytics users

#	Organisational Section	Department	Position	Sex	Seniority (y)
I1	Corporate Development	Employer Branding & Image	Team Lead	w	20 to 25
I2	Internal Corporate Consultancy	Management of Future Vacancies	Team Lead	m	15 to 20
I3	Insurance Claim Processing	Operational Workforce Management	Department Administration	w	30+
I4	Insurance Claim Processing	Operational Workforce Management	Head of Department	m	30+
I5	Human Resources	Organisation Design	Organisational Consulting	m	30+
I6	Human Resources	Organisation Design	Team Lead	m	0 to 5
I7	Human Resources	Organisation Design	Department Administration	w	25 to 30
I8	Human Resources	Personell Planning & Controlling	Associate	m	10 to 15
I9	Human Resources	Personell Planning & Controlling	Project Lead	m	15 to 20
I10	Human Resources	Recruiting, Development & Diversity	Team Lead	w	30+
I11	Human Resources	Strategic Workforce Planning	Senior Data Analyst	w	0 to 5
I12	Human Resources	Strategic Workforce Planning	Analyst	m	20 to 25

3.4.3 Research Object

The specific ML-based HRA tool investigated herein predicts individual voluntary turnover (excluding age-related reasons and termination on the part of the employer) probabilities within the next 6 months for each employee, using the Random Forest algorithm (Breiman 2001). The tool is trained on a fully anonymised dataset with monthly data over a three-year time horizon and includes 30 predictors originating from the same federal agency in which the interviews were conducted. Work-related predictors include commuting distance, sick days, salary, salary increases in recent years, seniority and others. Demographic data such as gender, age, number of children and education level are also included. The ML predictions are evaluated in an out-of-sample test dataset. Instead of treating the ML model as a black box, post-hoc XAI explanations at the local (employee-specific) and global (organisation-wide) levels are used to extract the effects of the predictors. The confusion matrix used to assess predictive accuracy, as well as some visualisations of the XAI results at the local and global level, were used as nudges during the interviews (see Figure 9). The visualisation of organisation-wide explanations shown in Figure 9 describes how a single predictor influences the employee turnover prediction (strength, positive/negative contribution) on average, considering all employees in that local interval (Apley and Zhu 2020). Additionally, the visualisation of employee-specific explanations breaks down the probability of voluntary turnover for each employee and quantifies it in terms of increasing or decreasing effects. The mean value represents the average employee turnover risk of all employees predicted in the model.

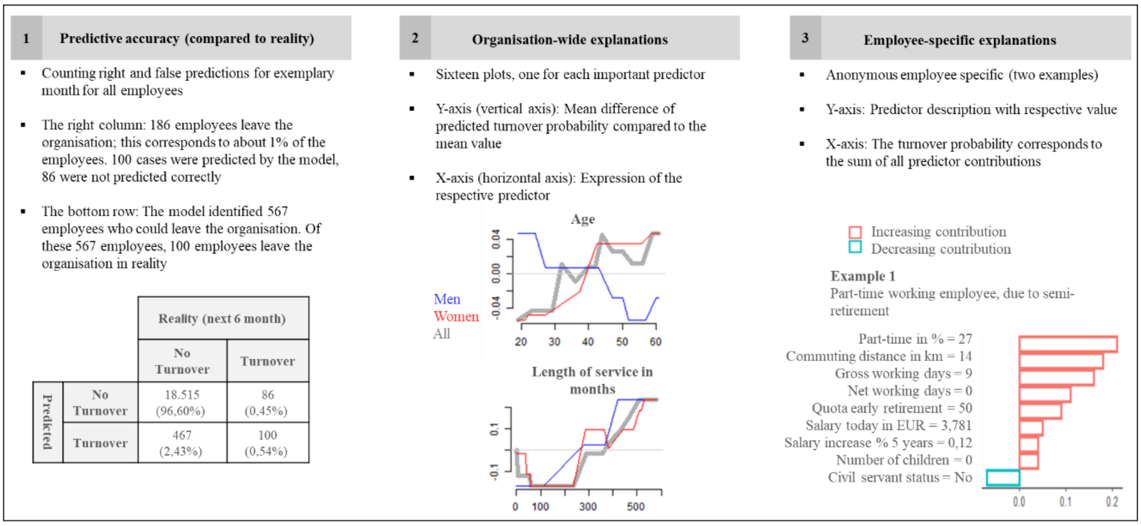

Figure 9: Information provided as nudges during the interviews: Predictive accuracy report, predictor effect explanations on the organisation-wide and employee-specific level

3.4.4 Data Analysis

Given the inductive nature of the study, we coded the transcripts manually, following the methodology proposed by Gioia et al. (2013), which has demonstrated its validity in numerous renowned publications over the last decade (e.g. Friedman and Ormiston 2022; Schuessler et al. 2023; Mula et al. 2024). All interview transcripts were coded independently by the first and second authors using MAXQDA[11] software. A total of 392 codes resulted. In the initial coding phase, we strictly adhered to the terms, phrases and descriptions of the interviewees, so that many first-order categories emerged. After eight interviews, both authors re-checked their coding to improve the reliability of the process and increase its rigour and authenticity. After coding all transcripts, first-order categories were compared against each other. Disagreements regarding interpretation, and thus coding, if any, were resolved through discussion. In the next step, for the second coding (axial coding), the first and second authors looked for similarities between and differences among the many first-order categories, in order to summarise and condense them. To this end, we went through each interview transcript as well as the first-order categories again. Subsequently, we discussed each passage and then reconciled different interpretations and conclusions to generate suitable second-order categories (Gioia et al. 2013).

Based on the TPB (Ajzen 1991), each of the second-order categories was independently assigned to PBC, attitude or norm (aggregated dimensions) by the first and second author (as determinants of an individual intention to adopt HRA) and then discussed. Subsequently, all second-order categories were critically reflected in correspondence with the framework provided by Vargas et al. (2018). The third author, who participated directly in project meetings and reviewed relevant project documents, critically reflected on the results in the final analysis step. Additionally, the coding of the entire interview material was repeated to verify validity. The re-coding of the first author, eleven months after the first coding, resulted in an overlap of 90.4% (intra-coder reliability). Coding by a person not previously involved in the research process resulted in an appropriate accordance of 79.0% (inter-coder reliability) (Miles and Huberman 1994). Figure 10 visualises all steps of the data analysis process.

[11] https://www.maxqda.com/.

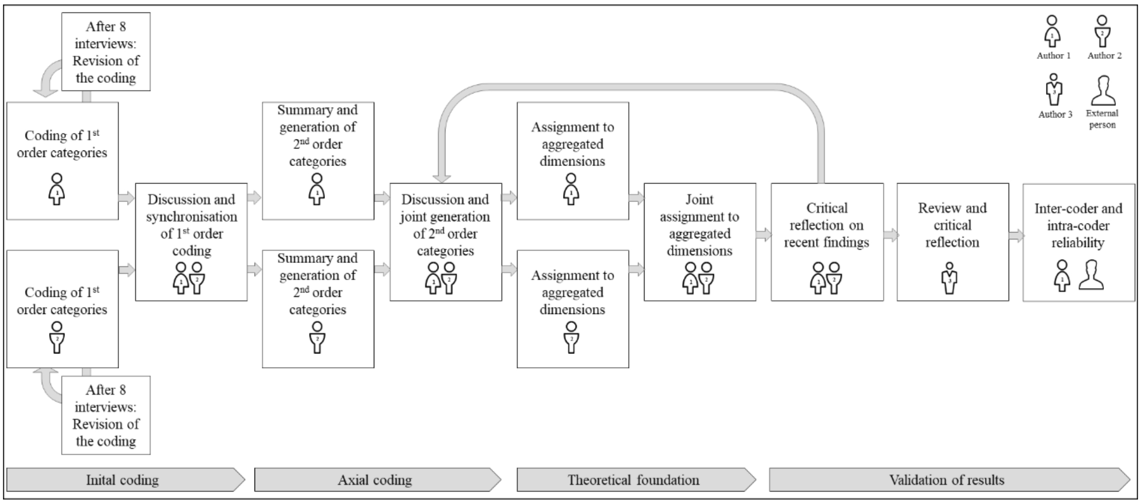

Figure 10: Interview coding process, including critical reflection steps to ensure reliability

The second-order categories and the aggregated dimensions formed the basis for the framework developed for the present study, and the first- and second-order categories, as well as the aggregate dimensions, became the basis for building the data structure (see Figure 11).

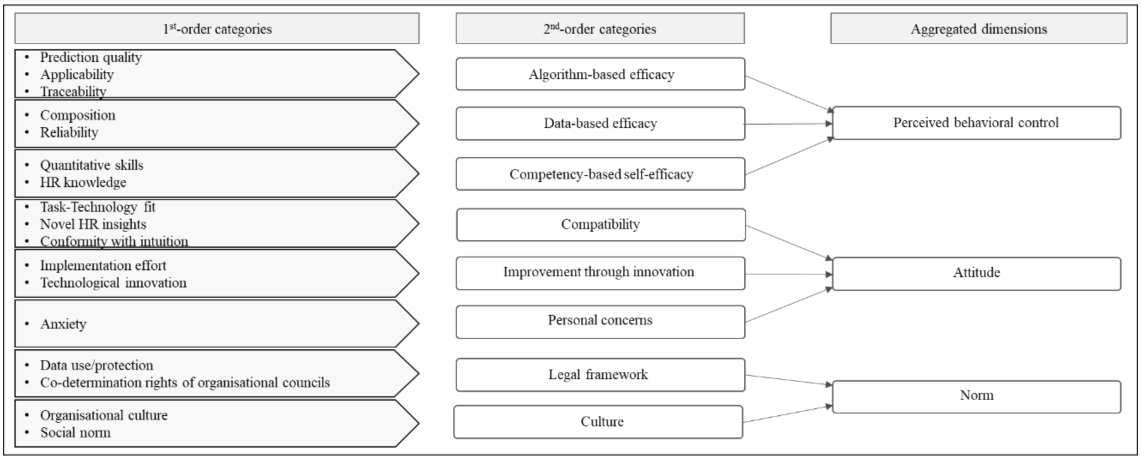

Figure 11: Data structure (first-order categories summarised by key topic)

3.5 Results

3.5.1 Factors Influencing the Individual Intention to Adopt ML-Based HR Analytics

The results regarding the beliefs and experiences that influence individuals' intention to adopt ML-based HRA (RQ1) are presented below. First, the findings on PBC are illustrated (see Table 11), following which, after describing attitudes towards the adoption of the tool (see Table 12), the perceived norms (see Table 13) of the interviewees are presented.

3.5.1.1 PBC

Algorithm-based efficacy describes all the capabilities and characteristics that interviewees attribute to and expect from an ML-based HRA tool, which allows them to utilise it in their daily work. Prediction quality captures the prediction accuracy of the tool, whereby the interviewees seem to require a sufficient level of prediction accuracy to view it as applicable. For our model, prediction accuracy is rated differently by I1 and I11. Another key factor for algorithm-based efficacy is traceability. The lines of reasoning by I10 reveal that the HRA tool's feasibility stems from explanations of the ML model and how this helps to optimise the organisational retention of top performers at the individual level. I12 points towards the XAI visualisations provided as an important distinction compared to popular generative Artificial Intelligence models such as ChatGPT. While scepticism towards these technologies is generally high, trust-building and achieving actionable insights can partially be attributed to traceability. The third driving factor for algorithm-based efficacy is applicability in practice. Among other things, the interviewees consider the extent to which the tool is mature and ready for use, its susceptibility to errors and the basic functions (e.g. the selection of different prediction periods) that it offers.

In addition, data-based efficacy plays an important role when forming the PBC. In our case, the opinions of the interviewees regarding the composition of the dataset differed widely. Some interviewees, like I2, identified missing and crucial predictors of voluntary turnover from their point of view, which had a critical impact on their evaluation of the tool. Others, like I9, were very satisfied with the included predictors. If they identified turnover predictors in the data, which they might consider important, data-based efficiency was considered high. Similarly, if the contribution and importance of the predictors in the XAI visualisations are as expected, then data-based efficiency seems to increase. Additionally, we find that dataset reliability plays an important role in the intention to adopt the HRA tool. For instance, I10 directly attributed the reliability of the department responsible for managing the database to the tool. Others, like I11 questioned the timeliness and quality of the data, its realism or rapid changes in the included turnover predictors.

In our study, competency-based self-efficacy reflects the beliefs an individual holds regarding their ability to use the ML-based HRA tool successfully in their daily work. Some interviewees, like I6, quickly understood the nudges shown, were interested in them and interpreted the information in detail. In their daily work, these people mostly take on analytical tasks and often have a background in statistics, which indicates that they have more pronounced quantitative skills. Others, like I8, were overwhelmed with the interpretation and had no deep interest in the information provided to them. In addition, the interviewees considered it necessary to have a certain level of HR knowledge, to be able to apply the results of the tool in practice and to derive potential application scenarios. The findings on our interviewees' PBC-related adoption of ML-based HRA tools, which are presented in Table 11, match interview insights into the dimensions related to the TPB.

Table 11: Interviewees' PBC related adoption of ML-based HRA tools

Example Insights	**1st-Order Categories**	**2nd-Order Categories**	**Aggegate Dimension**
"*... actually, quite impressive prediction quality.*" (I1, 34)	Prediction quality	Algorithm-based efficacy	PBC
"*... if you look at the absolute numbers, 467 and 100, prediction accuracy doesn't look so great.*" (I11, 102)			
"*I understood that the higher the absenteeism due to illness, the higher the probability that these people will leave the organisation, which would allow me as a personnel manager to conclude: How high is my sickness rate? [...] Unfortunately, my department has a very high sickness rate, and it would be exciting for me to see whether this has led to increased turnover – that the sick days were perhaps even the criterion.*" (I10, 104)	Traceability		
"*I do not know how to calculate the predictions. I do not know how the database must be prepared, how the model must be fed and so on. But if I look specifically at the XAI visualisations, I can already work with that. […] You first must deal with it [like a new software program] to be able to use it. [...] A little bit of scepticism is quite healthy, but ChatGPT has now increased our trust somewhat.*" (I12, 171)			
"*I would need 5 or 10 years and not the individual level of an employee, but I would have to look at the entire department, and I would have to look at certain levels, e.g. professional groups.*" (I11, 162)	Applicability		
"*All these flexible working time models with remote working etc. are not integrated into the model. After all, these affect 50% of our employees*." (I2, 108)	Composition of the dataset	Data-based efficacy	
"*These are very important predictors that I could then use for the future. So that would be very helpful, very helpful.*" (I9, 92)			
"*So you certainly calculated this from the data collected by Mr. […], I assume? From there, the data basis is safe for me – and from there I also trust in the numbers.*" (I10, 242)	Reliability		
"*So, for example, the economic situation, the issue of security, the issue of a personal family situation. The factors change. I hire someone who does not have any children, and then I know, well, maybe in 5 years there will be children. That means I cannot exert any influence. Likewise, what about changing health situations?*" (I11, 128)			
"*I understood the figures shown.*" (I6, 85)	Quantitative skills	Competency-based self-efficacy	
"*But at the moment, it slays me and everything – honestly.*" (I8, 249)			
"*I cannot say anything about that [how to adopt the tool specifically]. My colleagues in the HR department are more closely involved in this issue. I cannot assess the potential.*" (I12, 167)	HR knowledge		

3.5.1.2 Attitude

The interviewees' attitude towards the adoption of HRA was influenced, among other things, by its perceived compatibility. The assessment of the task technology fit was very different (see I3 and I7), with the added value and the concrete integrability of the ML-based HRA tool in everyday work being questioned and analysed. The interviewees' attitudes also seemed to be influenced by whether the results of the HRA tool revealed novel HR insights. Like I9, almost all interviewees stated that the tool could help identify at least some novel factors for employee voluntary turnover – and thus provide a basis for the development of personnel measures. It is notable that the consistency of the tools' predictions with personal intuition is an important determinant of attitude. Provided that the results matched the intuition, this manifested in an improved attitude, and vice versa.

In addition, considerations related to the improvement achieved by the tool seemed to have an impact on attitude. In our study, the extent to which implementation effort and technological innovation were perceived as impactful by the interviewees was important in this context (see Table 12). Some, like I4, felt that the innovative nature of the HRA tool enables new approaches to old challenges (such as demographic challenges) and improves previous processes (e.g. the quality of workforce planning). Essentially, innovation brings new perspectives and approaches. Others, like I11, critically questioned implementation efforts in terms of a cost-benefit trade-off.

A few interviewees questioned the personal consequences of adopting the HRA tool and evaluated them accordingly. I9 and I11 were particularly afraid that superiors use the HRA tool inappropriately (e.g. findings led to monitoring by the superior or mobbing), that false predictions led to negative effects (e.g. in the allocation of tasks) or that misunderstandings occurred. Findings relating to the interviewees' attitude to the adoption of ML-based HRA tools are presented in Table 12.

Table 12: Interviewees' attitude to the adoption of ML-based HRA tools

Example Insights	**1st-Order Categories**	**2nd-Order Categories**	**Aggegate Dimension**
"*I just wanted to add, because I think that our organisation is so big, that you do not have to look at individual employees. I cannot use that method at all.*" (I3, 109)	Task technology fit	Compatibility	Attitude
"*Through the tool, managers are encouraged to be active in their role.*" (I7, 362)			
"*Then I can look at this and analyse the most important factors that influence why this employee is leaving and use this to initiate optimisation.*" (I9, 120)	Novel HR insights		
"*Of course, this creates trust when you see that even without algorithms.*" (I3, 64)	Consistency with intuition		

Example Insights	**1st-Order Categories**	**2nd-Order Categories**	**Aggegate Dimension**
"*No, there must be a mistake. It says that the probability of turnover is higher for civil servants.*" (I5, 115)			
"*I see this as a great support, and it goes much further than what we could do in the past. […] You can draw insights from the data that give the organisation a positive kick in any case.*" (I4, 283)	Technological Innovation	Improvement through innovation	
"*I think it is great that such an approach has been found at all.*" (I6, 160)			
"*It is always nice to try something out, but of course, the question is then always cost and benefit. Does it bring us anything?*" (I11, 162)	Implementation Effort		
"*I am afraid of the surveillance now that the supervisor monitors me like this: Do I go or not?*" (I11, 206)	Anxiety	Personal concerns	
"*On the negative side, my responsible tasks could be taken away from me, because there would be a risk that I would leave the organisation.*" (I9, 212)			

3.5.1.3 Norm

The adoption of (ML-based) HRA tools is also limited by the '*Legal Framework*'. The interviewees stated that possible applications of the tool were severely limited or not possible due to legal conditions and the strict interpretation of data protection regulations in the public sector. Interestingly, some interviewees mentioned experiences with – from their point of view – overly strict data protection rules for historical organisational initiatives. For example, I8 stated that sensitive personal data should also be included in the tool and used for individual decision-making. Organisational councils have far-reaching co-determination rights that go beyond the law and enable employee representatives to object to various decisions affecting the entire organisation, thus obstructing adaptation. The interviewees perceived that initiatives based on employee data were – in principle – prevented. Among other things, organisational councils receive evaluations of all HR reports requested in the IT system, and they strictly ensure that each employee processes only the amount of information needed to complete tasks.

Culture is an important factor in the adoption of HRA (Vargas et al. 2018), where we distinguish between the social norm and organisational culture. During our interviews, some interviewees critically evaluated their social norm's compliance with the adoption and use of the HRA tool. For example, in terms of the individual employee's privacy, they questioned whether the analysis of personal data was acceptable from their point of view, or with whom the responsibility for ensuring appropriate use lay. Others, like I11, saw no threat to (personal) privacy. From the interviewees' responses, we were also able to find indications of the anchored organisational culture, which in our case tends to have a hindering effect on the HRA tool. The interviewees stated that there were many people with reservations and sceptics who viewed changes to previous processes or systems as negative; in addition, decision-making processes within the authority were often perceived as not rational and were very time-consuming. Moreover, the adoption of the HRA tool was a complicated undertaking because employees had difficulty dealing with predictions and uncertain expectations. Interview insights on subjective norms regarding adoption of ML-based HRA tools are presented in Table 13.

Table 13: Interviewees' subjective norms regarding the adoption of ML-based HRA tools

Example Insights	**1st-Order Categories**	**2nd-Order Categories**	**Aggegate Dimension**
"*Data protection is a very important topic in our organisation. [...] Because we run analyses here that can be evaluated on a personal basis, and conclusions can be drawn about a person.* " (I6, 180)	Data use/protection	Legal Framework	Norm
"*This is very sensitive data with which the tool works – highly explosive in terms of data protection. Therefore, it cannot be implemented in this form.*" (I7, 326)			
"*And when it comes to data protection […] I think [it] tends to protect those who have something to hide rather than benefit others. […] Instead of excluding variables, you might have to take other variables in addition*." (I8, 351-359)			
"*The problem is: The implementation of tools like this in-house must be approved by the organisational councils. From my work as an organisational consultant, I also know that software like this is not simply approved.*" (I5, 169)	Co-determination rights of organisational councils		
"*That would just be too much intrusion into my personal life for my supervisor to have that information to hand.*" (I9, 258)	Social norm	Culture	
"*My boss has all my data at his disposal. He knows how many children I have, and he also knows where I live. He also knows when I'm sick and how much I earn.*" (I11, 214)			
"*We have many doubters – there is not only the political thing in the house.*" (I7, 366)	Organisational culture		
"*The management always tries to be supportive, of course, but decisions are not made as quickly as in the private sector.*" (I9, 240)			

3.5.2 Impact of ML Characteristics

The results for how the characteristics of ML affect behavioural beliefs (RQ2) are presented below. Our findings are successively illustrated in terms of trialability, transparency, automation, self-learning capabilities and fairness, as well as their effect on beliefs and experiences.

3.5.2.1 Trialability Has an Impact on Attitude

Overall, we observe a positive effect of trialability on the intention to adopt the provided HRA tool. Similar to the findings of Vargas et al. (2018), our interviewees believe that it is important to try out the ML model before it is implemented in the organisation, in order to gain experience of using it. They argue that a high level of trial and error makes it easier to assess the accompanying consequences of actually applying the ML model, which in turn could lead to an increase or a decrease in one's attitude regarding the tool. On the one hand, trialability helps to assess whether the ML model provides a presumed improvement through innovation (technological innovation):

> "*I like to try something like this out in practice […]. ML does not really help here yet. I think we always have to make our own experiences with applications. […] They have to prove themselves in practice somewhere. And if they do not, then I have to analyse that. Where is the problem, or where does it not bring the benefit that I had hoped for? And, if necessary, I have to adapt it.*" (I4, 283)

On the other hand, trialability helps to mitigate any potential personal concerns of employees:

> "*For matters that are more critical, it is wise to first try things out, test them, see where adjustments can be made, involve the people and initially test it in a small area to then see how it is received [...] But having these sceptics around all the time makes everything a bit more difficult.*" (I11, 222)

3.5.2.2 ML Transparency Has an Impact on Both Attitude and PBC

We observe positive and negative effects of transparency on the intention to adopt the provided tool. At the beginning of the interviews, we asked the interviewees about their intention to adopt the employee turnover predictions in their daily work. Interestingly, most initially saw little to no application in the tool's predictions when it came to pure predictive accuracy without understanding the effects of the predictors:

> "*Unfortunately, I am not able to determine the value added because I have not performed any [proving] calculations [...]. Therefore, I could honestly plan better for the future based on historical data.*" (I9, 98)

However, the more transparency provided by the presentation of multiple predictor effects, the more diverse and extensive the applications identified by the interviewees (in their areas of responsibility), improving their attitude via the perception of compatibility of the tool and especially the personal task-technology fit. Besides reflecting on how the predictions could be used (e.g. for workforce planning and identifying future staff shortages), the interviewees also recognised that the tool provides explanations for turnover. Thus, it offers opportunities to either mitigate turnover at an individual level or derive strategic and organisation-wide initiatives that address employee wellbeing (e.g. increasing remote working opportunities) and employer attractiveness (e.g. increasing childcare offerings). The discussions in all interviews about possible applications of the tool in other HRM processes, made possible by transparency, indicate a higher algorithm-based efficacy.

In addition, providing more transparency can have a positive or a negative effect on one's attitude when the derived predictor effects contradict personal intuition (compatibility). On the one hand, our interviewees found contradicting evidence useful in questioning their personal intuition:

> "*But it definitely brings insights that straighten out the picture and probably bring it closer to reality. Yes, I would use it if I had to decide for my hotdog stand.*" (I1, 135)

On the other hand, a few interviewees questioned the functionality of the provided tool when identifying evidence that contradicted their own intuition (conformity with intuition, see Table 12). Furthermore, our results suggest that these interviewees demanded a high degree of traceability to help them understand the underlying calculations of the ML model (algorithm-based efficacy):

> "*I [...] want to understand what is happening behind the system [...] In Excel, you can see how the calculation is done and what the result will be. With machine learning, you probably won't be able to see it that way. The machine learns based on the data and then outputs something. So, I always need a certain level of traceability for each step.*" (I9, 294)

To summarise, we find that transparency influences attitudes via the perception of compatibility in two ways (personal task-technology fit and conformity with intuition), as well as PBC via algorithm-based efficacy, also in two ways (applicability and traceability).

3.5.2.3 Degree of Automation through ML Decision-Making Influences Attitude and PBC

We mostly observe a negative effect of the degree of automation on the intention to adopt the provided ML model. All interviewees agreed that decisions should only be augmented with the help of the tool and that a fully automated decision-making process should not be implemented. Several reasons regarding attitude, especially personal concerns, were given for this, such as the fact that the interpersonal component must not be lost, especially when decisions are made on an individual basis:

> "*At the top level, they want numbers, and there's also the risk that when they see those numbers, they do not want to deviate from them […]. However, the human factor, and the perspective and the focus on the individual employees, is simply lost as a result. The decision-makers who normally have management responsibility, who actually manage people, have to look at the results.*" (I1, 52)

I4 pointed out that automation is only useful if the model does not make a single mistake. This in turn is reflected in the expected accuracy of the tool (algorithm-based efficacy):

> "*[For automation], the probability of correct predictions is not yet high enough, not until the hundred per cent mark is reached. Until then, decisions are up to personnel analysis by management – instead of letting the machines think completely.*" (I4, 275)

The interviewees believed that the responsibility and rational towards decisions lies with humans (an ML-augmented decision process) and questioned whether the provided ML model is suitable for drawing the right conclusions and deriving appropriate actions from a prediction. This translates to a low perceived applicability (algorithm-based efficacy):

> "*If you were to go only by the machine: a woman has a salary of 3,000 euros. We will just raise it to 4,000 euros – but a man does not get that raise. [...] I would see it critically in the first instance. In any case, it does not replace the interpersonal connection. Well, I do not work together with the machine, especially not in a subordinate relationship. Ultimately, such a decision must be made by a manager.*" (I7, 402)

3.5.2.4 The Self-Learning Capabilities of ML Affect PBC

Unexpectedly, we identified the perceived learning capabilities of the provided ML model as a further relevant ML characteristic influencing the algorithm-based efficacy (PBC). A few interviewees associated continuous learning with ML and expected continuously increasing accuracy due to future learning iterations with more data or feedback loops:

> "*[With] ML and Artificial Intelligence work – as far as I have now generally heard – the more you feed, let's say, the machine with information, the better it becomes. And that's exactly the direction it should go if you use it more often and feed it with more and more data. It will get better and better, and that will also reduce the error rate, in my opinion.*" (I9, 182)

Interestingly, some of the interviewees translated the automated self-learning characteristics they were aware of from a reinforcement learning ML model in another context to this specific ML model, without knowing whether these feedback loops were actually implemented:

> "*[ML] ... is a self-learning system, and the more often I run it, the better my predictions become. In this respect, if I have understood correctly, we are still at the start. And the more data is fed in and compared with real things, the more accurate the predictions will be – at least that's what I would expect.*" (I2, 85)

3.5.2.5 (Un-)Fairness Does Not Affect the Intention to Adopt

As noted in the literature review, increased ML transparency can also affect perceptions of ML fairness. In the interviews, we specifically asked about the fairness perception in hypothetical scenarios (e.g. What requirements do you have for the model in terms of fairness or equal opportunity? Would you remove certain data from the dataset, for example, for reasons of fairness or equal opportunity? From the position of your supervisor making decisions about you, do you have any reservations or concerns about using the model?). Interestingly, none of the interviewees mentioned significant caveats regarding fairness aspects. For example, excluding protected group variables from the dataset was not suggested by any interviewee. We were able to ascertain this even after providing a list of predictors used in the ML model as well as XAI visualisations that (1) listed protected group variables such as gender or age and other data that require extensive protection, such as health-related information, (2) clearly documented differences between protected group variables and their impact and (3) were considered the basis for local (employee-specific) or global (organisation-wide) decision-making – and thus varying degrees of impact on individual employees. Several arguments were made by the interviewees as to why the HRA tool in its current state is fair and no adjustments are needed. First, I9 referred to the objectivity of the data and the responsibility for any consequences:

> "*You cannot influence the fact that our organisation is over 70% women, so you cannot do anything by saying that we now have to hire only men. That would be discriminatory. That is why I do not think it is so bad. Those are the facts, that is the database, you cannot change that. Or that older workers are less likely to quit. As a human being, as a decision-maker, you also have the information, and you have to interpret it accordingly.*" (I9, 280)

Second, I1 made a similar argument, pointing out the possible lower prediction accuracy of the tool when predictors are eliminated. The interviewee argued that differences are not unfair if they are based on differences between protected groups that can be explained by real facts, which he exemplified in terms of intergenerational differences:

> "*My father was in the same company for 30 years, my mother worked in the same company for over 40 years. So that is the thing, for me, that would be unthinkable. I would not exclude predictors like age or gender […]. I can understand that you want to leave such factors out so as not to discriminate against anyone […], but it would also just be out of touch with reality. […]. I would claim that there are significant differences, and that tells me that it must not be left out at all.*" (I1, 151)

Overall, we found no evidence that the interviewees had changed their intention to adopt the HRA tool due to the different treatment of women or men, or younger and older employees. This can be explained by the above statement that potentially unfair discriminatory decisions should be corrected by human judgment in an augmented (non-automated) decision-making process.

3.5.3 Refined Model: Individual Intention to Adopt HR Analytics

The results of our study are summarised in a qualitative model, as illustrated in Figure 12. Vargas et al.'s (2018) framework forms the basic structure on which the various factors influencing PBC, attitude and norms are concretised. As a further addition, the influences of ML characteristics emerge. Please note that ML characteristics have effects on zero (fairness), one (self-learning capabilities) or two (transparency, automation and trialability) constructs of behavioural beliefs.

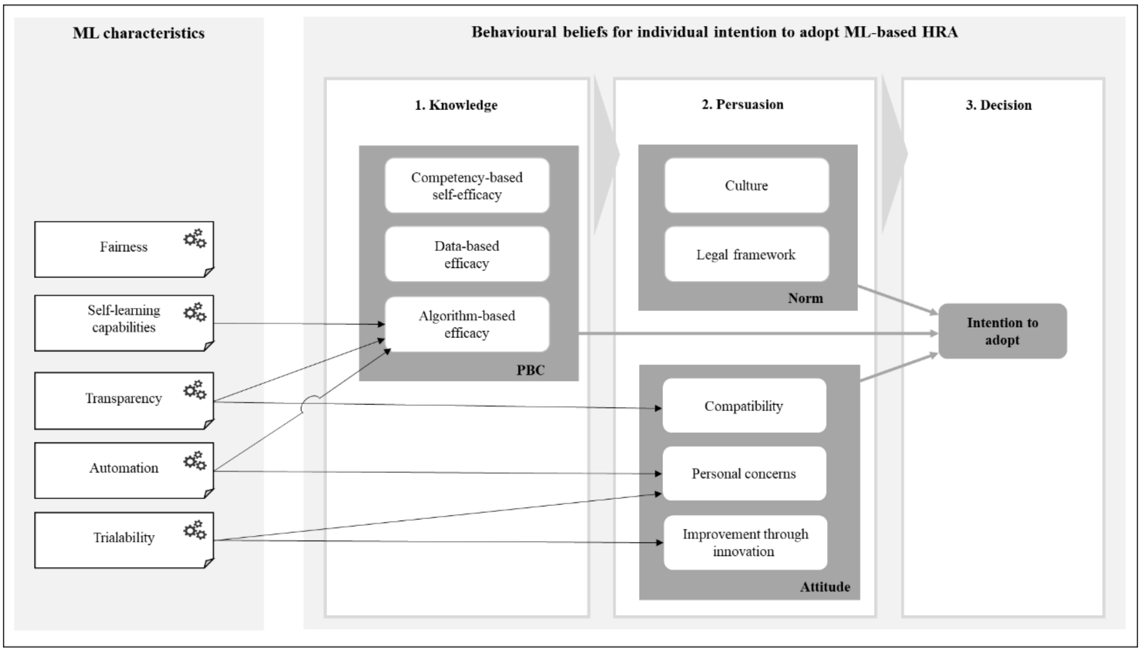

Figure 12: Proposed qualitative model for individual intention to adopt HRA based on ML characteristics

3.6 Discussion and Implications

Notwithstanding the asserted importance of HRA, research examining its impact on organisational performance remains underdeveloped (Marler and Boudreau 2017). While recent studies find evidence for the effects of HRA and organisational performance, this link is mediated by an organisational shift to more evidence-based management practice. Moreover, it is argued that HRA can only provide a benefit for an organisation when predictions and estimations are incorporated into neutral and evidence-driven decision-making (McCartney and Fu 2022). Evidently, a respective shift requires a congruent employee mindset and therefore a strong intention to incorporate HRA into their daily work. Our study contributes to this ongoing debate by extending and contextualising current knowledge on the adoption of ML-based HRA for a specific use case.

3.6.1 PBC, Attitude and Norms Influence an Individual's Intention to Adopt HRA

Regarding salient beliefs and experiences, Vargas et al. (2018) find five factors determining the individual adoption of HRA: technology self-efficacy (PBC), quantitative self-efficacy (PBC), attitude towards using HRA, social influence and tool trialability. Vargas (2016) investigates a larger number of possible factors influencing the user level of adoption, whereby general self-efficacy and data availability, which were queried in the survey with narrowly specified items, showed no significant influence. Therefore, we investigate the personal perspectives, experiences and spontaneous reactions of knowledgeable employees in a specific use case with field data. This particularly provides a lens for a deeper understanding of the individual adoption of ML-based HRA. For example, we find evidence that interviewees with higher quantitative skills, as well as overall competency-based self-efficacy (e.g. HR knowledge), were more open to incorporating the displayed HRA tool in their work. In addition to technological aspects, the input data on which the ML-based HRA tool is trained was highly important to the interviewees. We therefore suggest that data-based efficacy, as an aggregation of the composition and reliability of the dataset, is another important dimension of a potential user's efficacy. The findings published by Omrani et al. (2022) suggest similar relationships in terms of data, albeit their study argues that concerns about discrimination in the use of Artificial Intelligence reduce trust. In addition, we find evidence that attitudes toward the adoption of HRA are made up of a wide variety of aspects. These can be divided into three categories, namely the assessment of the tool's compatibility in daily work, an assessment of the potential for improving the tool in organisational processes and personal concerns. Venkatesh et al. (2003) find similar results in their model of technology use. In their work, performance expectancy, as the "*extent to which an individual believes that using the system will help them improve their job performance*", represents a relevant factor similar to the perceived usefulness of the *Technology Acceptance Model* (Davis 1989). Regarding the norm, the interview data also divides this factor into legally established norms and (organisationally) culturally determined aspects.

Proposition 1: For ML-based HRA, an understanding of related studies is not sufficient to explain individual adoption. Instead, we propose additional important determinants for PBC (data-based and algorithm-based efficacy), attitude (compatibility of tools and tasks, personal concerns, improving practices through innovation) and norm (organisational culture and legal framework).

3.6.2 Most ML Characteristics Have an Influence on Behavioural Beliefs

Furthermore, our results suggest that several additional ML characteristics drive perceived algorithm-based efficacy as well as attitudes to the use of the displayed ML tool. First, to make ML-based HRA useful, predictors' diagnostic results – provided by the XAI visualisations – are an important facilitator in terms of coalescing employee turnover predictions (Chowdhury et al. 2022). Identifying additional uses of the HRA tool when understanding the causes of employee turnover suggests a more evidence-based management practice, which is theorised as an important enabler of HRA in an organisation (McCartney and Fu 2022). The studies by Kim et al. (2023) and Haque et al. (2023) reveal that XAI visualisations in particular contribute to user understanding and adoption, when appropriately designed. To summarise, in most cases, higher transparency leads to a higher attitude and PBC. We thus provide an empirical example demonstrating that with sufficient ML transparency, the various burdens on users (emotional, mental, prejudices, etc.) (Park et al. 2021) can be overcome when introducing ML-based HRA. However, in line with other research (Schmidt et al. 2020), we also find that these effects can be reversed when the rational explanations of the model and the reasoning of experts contradict each other.

Second, our interviewees were reluctant to automate an entire decision, for example a promotion, by delegating it to the HRA tool, as most of them did not expect the respective tool to possess the necessary skills to solve the task adequately on its own. This finding is similar to the results by Dietvorst et al. (2018), who identified a significant aversion to fully automated predictive analytics tools that vanishes when participants get at least some degree of control over the underlying decision. Lee and Cha (2023) confirm this notion by showing that choosing augmentation over automation is one of the two key factors in adopting Artificial Intelligence recruitment systems.

Third, we observe a difference in the beliefs of the interviewees, who expect the displayed HRA tool to have self-learning capabilities or not. In sum, our empirical data indicates that interviewees are more forgiving of an error-prone prediction in the first case, as maybe because they expect the HRA tool to subsequently improve upon its past mistakes and thus increase algorithm-based efficacy. Note that this finding is in line with Reich et al. (2023) and Berger et al. (2020), both of whom identify self-learning capabilities as an important factor in mitigating algorithm aversion. Our study extends these interesting points by the fact that self-learning ability may be taken for granted by using the ML term, while such abilities (e.g. reinforcement learning) are not even implemented.

Fourth, as proposed by Vargas et al. (2018), our interviewees were interested in trying out the displayed HRA tool to assess its capabilities and then form an attitude on it. In addition, indicators of initial anxiety about the ML-based HRA tool's capabilities were apparent (see Table 12), which can be addressed with trialability. This finding is in line with the *Innovation Diffusion Theory* (Rogers 2003). In summary, we therefore propose:

Proposition 2: Several ML characteristics influence attitude and PBC in relation to the intention to adopt ML-based HRA: (a) the degree of transparency created, (b) the choice of automated usage, (c) the implementation of self-learning capabilities and (d) the enabling of trialability.

Consistent with Neumann et al. (2022), we find no reference in the interviews to ethical considerations regarding the adoption of the ML-based HRA tool in our empirical setting from public sector. Our results show that fairness and non-discrimination were not critically questioned, even when potential biases were highlighted by XAI visualisations and the interviewees were explicitly asked about them. This outcome is alarming, as HRA, and especially ML, can foster discrimination and create various risks for employees and the organisation (Tursunbayeva et al. 2022). For example, according to the General Data Protection Regulation of the European Union, the use of an ML model that includes protected class variables for individual decision-making can be considered a legal case of discrimination, referred to as '*Disparate Treatment*' (Goodman and Flaxman 2017). Lee and Cha (2023) confirm that solving the fairness problem remains complex, even if this complexity mitigates discovering an unfair decision basis.

Proposition 3: Fairness does not matter for the individual deciding whether to adopt ML-based HRA and must be ensured by other appropriate measures.

3.6.3 Implications for Practice

In practice, organisations seeking to leverage the potential of efficiency gains through ML-based HRA might try to increase adoption at the individual level. Our results reveal that various adjustable modifiers exist during adoption, in particular the degree of automation in algorithm-based decision-making and provided transparency. Most importantly, technical measures (such as XAI) can positively or negatively influence both PBC and attitude, because providing understandable visualisation allows the user to compare the included predictors, as well as their effects with their intuition.

However, in trying to increase the intention to adopt ML-based HRA on an individual level, organisations should be careful to avoid pitfalls. For instance, negative examples have already demonstrated that biases can lead to unfair decisions based on ML (e.g. Alon-Barkat and Busuioc 2023). With the risk of resulting high social and economic damage, the consideration of ethical challenges is necessary in HRA projects (Langer and König 2021; Edwards et al. 2022). As legislation for the responsible use of ML comes into force soon (AI HLEG EU 2019), organisations need to address such potential unfairness proactively. Thus, our finding, namely that ethical considerations and fairness of HRA in the early adoption stages were not challenged by the interviewees, is alarming and should therefore be paid careful attention in practice. Neumann et al. (2022) note that specifically the early adoption phases of ML applications are characterised by (1) a focus on positive business cases, (2) reliance on external partners, (3) change management processes to increase acceptance and (4) little to no real recognition of ethical considerations such as algorithm accountability and fairness. Thus, we specifically advise organisations to ensure proactively the inclusion of ethical considerations in the early stages of adoption and to implement internal policies and approval procedures with the help of internal or external expertise.

Ultimately, the responsible use of ML-based HRA can only be achieved when HR professionals have the knowledge necessary to evaluate ML models critically, based on the transparency provided by technical measures such as XAI visualisations and internal guidelines (Langer and König 2021). However, Vargas et al. (2018) note that HR professionals have low levels of quantitative self-efficacy (fear of maths/statistics, lack of quantitative training, low awareness of analytics, lack of resources and organisational support to promote analytics and its tools). Our results extend these findings, which suggest investing in training initiatives that demonstrate the importance of achieving ML transparency and in turn encourage the acquisition of skills specifically to interpret performance statistics of ML algorithms or XAI visualisations.

3.6.4 Limitations and Further Research

There are two main points that limit the findings of this study. First, our qualitative approach is based on the manual coding of interview transcripts; however, we took several measures to ensure the validity of our findings during the coding process and after the final analysis (see Figure 10). For example, the credibility of our findings was established by independent coding by two of the authors in three coding steps. In addition, our results were critically reflected on the basis of existing evidence (Vargas et al. 2018) and by the third author. The findings were verified by inter-coder and intra-coder reliability (Miles and Huberman 1994).

Second, while the methodological choice of a single case study has a solid foundation in HRM, and recent studies using this method advance the field considerably (e.g. Ellmer and Reichel 2021; van den Broek et al. 2021; Remneland Wikhamn et al. 2023), this methodological choice limits the transferability of our findings (Flyvbjerg 2006). Nonetheless, it offers the advantages of an in-depth investigation of HRM practices with a heterogeneous interviewee population (e.g. diverse backgrounds and experience) and an examination of deep cause-effect relationships (from ML characteristics to HRA adoption) that are overlooked in broader studies. In our particular case, the results thus pave the way for future quantitative studies that can explain the individual adoption of HRA more holistically and further develop the previous framework by Vargas et al. (2018), which can only explain about 35% of the observed variance. To achieve this, the exploratory and qualitative nature of our study leaves the following concrete possibilities for future research. First, future studies should examine multiple organisations to further validate the transferability of the three propositions for individual HRA adoption. Second, we invite future research to formulate and quantitatively test hypotheses based on our proposed qualitative model. Especially, the effects of the automated usage of ML predictions and ML transparency provide interesting opportunities in this regard, as they both affect PBC as well as attitude. In addition, our study is not able to provide insights into the effect strength of the assumed causal relationships between ML characteristics and the intention to adopt. Third, we focus on the first implementation of an ML-based HRA tool, which means that the key beliefs and experiences identified, as well as underlying

ML characteristics, may not apply to a more mature stage of ML adoption. Therefore, given that Information Systems research has found a considerable number of factors influencing the intention to use HRA (e.g. Mahmud et al. 2022), future research could investigate whether the effects and significance of certain factors change over the course of the implementation and utilisation phase. For example, does the importance of ML transparency decline as users of ML-based HRA gain experience over time and learn that the system provides (in-)accurate results? Fourth, we agree with the widespread view that HRM systems need to be tailored to the individual case (e.g. Remneland Wikhamn et al. 2023), which is why we also call for more qualitative research examining the individual adoption of technological advances in ML-based HRA.

3.7 Conclusion

In contrast to existing technological tools, ML-based HRA generates unique challenges, most notably the potential opacity of the rationality used by models to formulate predictions, as well as the potential to automate HRM decision-making fully. This study provides deeper insights into behavioural beliefs determining the decision to adopt ML-based HRA from an individual perspective and sheds light on how ML characteristics affect it. Based on the *Focused Interview* methodology, we introduce novel propositions and an extended qualitative framework with new constructs of important factors from the perspective of end-users of individual HRA adoption. Investigating the lines of reasoning also reveals that potential ML model users do not include fairness considerations in their decision to neglect or adopt the tool. We hope our findings help to guide both the interdisciplinary research on HRA and organisations to a successful path in their mission to achieve the responsible proliferation of ML-based HRA.

3.8 List of References

AI HLEG EU (2019): High-Level Expert Group Artificial Intelligence (European Union) – Ethics Guidelines for Trustworthy AI. Published on April 8, 2019. Available online at: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai (retrieved on July 7, 2025).

Ajzen, Icek (1991): The Theory of Planned Behavior. In: Organizational Behavior and Human Decision Processes 50 (2), pp. 179–211. DOI: 10.1016/0749-5978(91)90020-t.

Ajzen, Icek (2002): Perceived Behavioral Control, Self-Efficacy, Locus of Control, and The Theory of Planned Behavior. In: Journal of Applied Social Psychology 32 (4), pp. 665–683. DOI: 10.1111/j.1559-1816.2002.tb00236.x.

Alon-Barkat, Saar; Busuioc, Madalina (2023): Human–AI Interactions in Public Sector Decision Making: “Automation Bias” and “Selective Adherence” to Algorithmic Advice. In: Journal of Public Administration Research and Theory 33 (1), pp. 153–169. DOI: 10.1093/jopart/muac007.

Angrave, David; Charlwood, Andy; Kirkpatrick, Ian; Lawrence, Mark; Stuart, Mark (2016): HR and Analytics: Why HR is Set to Fail the Big Data Challenge. In: Human Resource Management Journal 26 (1), pp. 1–11. DOI: 10.1111/1748-8583.12090.

Apley, Daniel W.; Zhu, Jingyu (2020): Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models. In: Journal of the Royal Statistical Society Series B: Statistical Methodology 82 (4), pp. 1059–1086. DOI: 10.1111/rssb.12377.

Arrieta, Alejandro B.; Díaz-Rodríguez, Natalia; Del Ser, Javier; Bennetot, Adrien; Tabik, Siham; Barbado, Alberto; Garcia, Salvador; Gil-Lopez, Sergio; Molina, Daniel; Benjamins, Richard; Chatila, Raja; Herrera, Francisco (2020): Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. In: Information Fusion 58, pp. 82–115. DOI: 10.1016/j.inffus.2019.12.012.

Bandura, Albert (1977): Self-efficacy: Toward a Unifying Theory of Behavioral Change. In: Psychological Review 84 (2), pp. 191–215. DOI: 10.1037//0033-295x.84.2.191.

Basu, Shubhabrata; Majumdar, Bishakha; Mukherjee, Kajari; Munjal, Surender; Palaksha, Chandan (2023): Artificial Intelligence–HRM Interactions and Outcomes: A Systematic Review and Causal Configurational Explanation. In: Human Resource Management Review 33 (1), p. 100893. DOI: 10.1016/j.hrmr.2022.100893.

Berger, Benedikt; Adam, Martin; Rühr, Alexander; Benlian, Alexander (2020): Watch Me Improve – Algorithm Aversion and Demonstrating the Ability to Learn. In: Business & Information Systems Engineering 63 (1), pp. 55–68. DOI: 10.1007/s12599-020-00678-5.

Böhmer, Nicole; Schinnenburg, Heike (2023): Critical Exploration of AI-driven HRM to Build Up Organizational Capabilities. In: Employee Relations: The International Journal 45 (5), pp. 1057-1082. DOI: 10.1108/ER-04-2022-0202.

Breiman, Leo (2001): Random Forests. In: Machine Learning 45 (1), pp. 5–32. DOI: 10.1023/A:1010933404324.

van den Broek, Elmira; Sergeeva, Anastasia; Huysman Vrije, Marleen (2021): When the Machine Meets the Expert: An Ethnography of Developing AI for Hiring. In: MIS Quarterly 45 (3), pp. 1557–1580. DOI: 10.25300/MISQ/2021/16559.

Burrell, Jenna (2016): How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms. In: Big Data & Society 3 (1), pp. 1–12. DOI: 10.1177/2053951715622512.

Busuioc, Madalina (2021): Accountable Artificial Intelligence: Holding Algorithms to Account. In: Public Administration Review 81 (5), pp. 825–836. DOI: 10.1111/puar.13293.

Chatterjee, Sheshadri; Rana, Nripendra P.; Dwivedi, Yogesh K.; Baabdullah, Abdullah M. (2021): Understanding AI Adoption in Manufacturing and Production Firms Using an Integrated TAM-TOE Model. In: Technological Forecasting and Social Change 170, p. 120880. DOI: 10.1016/j.techfore.2021.120880.

Chowdhury, Soumyadeb; Joel-Edgar, Sian; Dey, Prasanta Kumar; Bhattacharya, Sudeshna; Kharlamov, Alexander (2022): Embedding Transparency in Artificial Intelligence Machine Learning Models: Managerial Implications on Predicting and Explaining Employee Turnover. In: The International Journal of Human Resource Management 34 (14), pp. 1–32. DOI: 10.1080/09585192.2022.2066981.

Coolen, Patrick; van den Heuvel, Sjoerd; van de Voorde, Karina; Paauwe, Jaap (2023): Understanding the Adoption and Institutionalization of Workforce Analytics: A Systematic Literature Review and Research Agenda. In: Human Resource Management Review 33 (4), p. 100985. DOI: 10.1016/j.hrmr.2023.100985.

Davenport, Thomas H.; Harris, Jeanne; Shapiro, Jeremy (2010): Competing on Talent Analytics. In Harvard Business Review 88 (10), pp. 2–6. Available online at: https://www.researchgate.net/publication/47369355_Competing_on_talent_analytics (retrieved on July 7, 2025).

Davis, Fred D. (1989): Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. In: MIS Quarterly 13 (3), p. 319-340. DOI: 10.2307/249008.

Desouza, Kevin C.; Dawson, Gregory S.; Chenok, Daniel (2020): Designing, Developing, and Deploying Artificial Intelligence Systems: Lessons from and for the Public Sector. In: Business Horizons 63 (2), pp. 205–213. DOI: 10.1016/j.bushor.2019.11.004.

Di Vaio, Assunta; Hassan, Rohail; Alavoine, Claude (2022): Data Intelligence and Analytics: A Bibliometric Analysis of Human–Artificial Intelligence in Public Sector Decision-Making Effectiveness. In: Technological Forecasting and Social Change 174, p. 121201. DOI: 10.1016/j.techfore.2021.121201.

Dietvorst, Berkeley J.; Simmons, Joseph P.; Massey, Cade (2018): Overcoming Algorithm Aversion: People will Use Imperfect Algorithms if They can (Even Slightly) Modify Them. In: Management Science 64 (3), pp. 1155–1170. DOI: 10.1287/mnsc.2016.2643.

Edwards, Martin R.; Charlwood, Andy; Guenole, Nigel; Marler, Janet (2022): HR Analytics: An Emerging Field Finding Its Place in the World alongside Simmering Ethical Challenges. In: Human Resource Management Journal 34 (2), pp. 326–336. DOI: 10.1111/1748-8583.12435.

Einola, Katja; Khoreva, Violetta (2023): Best Friend or Broken Tool? Exploring the Co-Existence of Humans and Artificial Intelligence in the Workplace Ecosystem. In: Human Resource Management 62 (1), pp. 117–135. DOI: 10.1002/hrm.22147.

Ellmer, Markus; Reichel, Astrid (2021): Staying Close to Business: The Role of Epistemic Alignment in Rendering HR Analytics Outputs Relevant to Decision-Makers. In: The International Journal of Human Resource Management 32 (12), pp. 2622–2642. DOI: 10.1080/09585192.2021.1886148.

Fishbein, Martin; Ajzen, Icek (2010): Predicting and Changing Behavior: The Reasoned Action Approach. New York, New York: Psychology Press.

Flyvbjerg, Bent (2006): Five Misunderstandings about Case-Study Research. In: Qualitative Inquiry 12 (2), pp. 219–245. DOI: 10.1177/1077800405284363.

Friedman, Nicola; Ormiston, Jarrod (2022): Blockchain as a Sustainability-Oriented Innovation?: Opportunities for and Resistance to Blockchain Technology as a Driver of Sustainability in Global Food Supply Chains. In: Technological Forecasting and Social Change 175, p. 121403. DOI: 10.1016/j.techfore.2021.121403.

Gioia, Dennis A.; Corley, Kevin G.; Hamilton, Aimee L. (2013): Seeking Qualitative Rigor in Inductive Research. In: Organizational Research Methods 16 (1), pp. 15–31. DOI: 10.1177/1094428112452151.

Glikson, Ella; Woolley, Anita Williams (2020): Human Trust in Artificial Intelligence: Review of Empirical Research. In: Academy of Management Annals 14 (2), pp. 627–660. DOI: 10.5465/annals.2018.0057.

Goodman, Bryce; Flaxman, Seth (2017): European Union Regulations on Algorithmic Decision-Making and a "Right to Explanation". In: AI Magazine 38 (3), pp. 50–57. DOI: 10.1609/aimag.v38i3.2741.

Haque, A. K. M. Bahalul; Islam, A. K. M. Najmul; Mikalef, Patrick (2023): Explainable Artificial Intelligence (XAI) from a User Perspective. A Synthesis of Prior Literature and Problematizing Avenues for Future Research. In: Technological Forecasting and Social Change 186, p. 122120. DOI: 10.1016/j. techfore.2022.122120.

Hunkenschroer, Anna L.; Luetge, Christoph (2022): Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. In: Journal of Business Ethics 178 (3), pp. 977–1007. DOI: 10.1007/s10551-022-05049-6.

Kellogg, Katherine C.; Valentine, Melissa A.; Christin, Angéle (2020): Algorithms at Work: The New Contested Terrain of Control. In: Academy of Management Annals 14 (1), pp. 366–410. DOI: 10.5465/annals.2018.0174.

Kim, Doha; Song, Yeosol; Kim, Songyie; Lee, Sewang; Wu, Yanqin; Shin, Jungwoo; Lee, Daeho (2023): How Should the Results of Artificial Intelligence Be Explained to Users? – Research on Consumer Preferences in User-Centered Explainable Artificial Intelligence. In: Technological Forecasting and Social Change 188, p. 122343. DOI: 10.1016/j.techfore.2023.122343.

Langer, Markus; König, Cornelius J. (2021): Introducing a Multi-Stakeholder Perspective on Opacity, Transparency and Strategies to Reduce Opacity in Algorithm-based Human Resource Management. In: Human Resource Management Review 33 (1), p. 100881. DOI: 10.1016/j.hrmr.2021.100881.

Lee, ChangHyun; Cha, KyungJin (2023): FAT-CAT – Explainability and Augmentation for an AI System: A Case Study on AI Recruitment-System Adoption. In: International Journal of Human-Computer Studies 171, p. 102976. DOI: 10.1016/j.ijhcs.2022.102976.

Mahmud, Hasan; Islam, A.K.M. Najmul; Ahmed, Syed Ishtiaque; Smolander, Kari (2022): What Influences Algorithmic Decision-Making? A Systematic Literature Review on Algorithm Aversion. In: Technological Forecasting and Social Change 175, p. 121390. DOI: 10.1016/j.techfore.2021.121390.

Margherita, Alessandro (2022): Human Resources Analytics: A Systematization of Research Topics and Directions for Future Research. In: Human Resource Management Review 32 (2), p. 100795. DOI: 10.1016/j.hrmr.2020.100795.

Marler, Janet H.; Boudreau, John W. (2017): An Evidence-based Review of HR Analytics. In: The International Journal of Human Resource Management 28 (1), pp. 3–26. DOI: 10.1080/09585192.2016.1244699.

McCartney, Steven; Fu, Na (2022): Bridging the Gap: Why, How and When HR Analytics Can Impact Organizational Performance. In: Management Decision 60 (13), pp. 25–47. DOI: 10.1108/MD-12-2020-1581.

Meijerink, Jeroen; Bondarouk, Tanya (2023): The Duality of Algorithmic Management: Toward a Research Agenda on HRM Algorithms, Autonomy and Value Creation. In: Human Resource Management Review 33 (1), p. 100876. DOI: 10.1016/j.hrmr.2021.100876.

Meijerink, Jeroen; Boons, Mark; Keegan, Anne; Marler, Janet (2021): Algorithmic Human Resource Management: Synthesizing Developments and Cross-Disciplinary

Insights on Digital HRM. In: The International Journal of Human Resource Management 32 (12), pp. 2545–2562. DOI: 10.1080/09585192.2021.1925326.

Merton, Robert K.; Kendall, Patricia L. (1946): The Focused Interview. In: American Journal of Sociology 51 (6), pp. 541–557. DOI: 10.1086/219886.

Miles, Matthew B.; Huberman, A. Michael (1994): Qualitative Data Analysis. An Expanded Sourcebook. 2. Edition. Thousand Oaks, California: Sage.

Mula, Claire; Zybura, Nora; Hipp, Thomas (2024): From Digitalized Start-up to Scale-up: Opening the Black Box of Scaling in Digitalized Firms towards a Scaling Process Framework. In: Technological Forecasting and Social Change 202, p. 123275. DOI: 10.1016/j.techfore.2024.123275.

Neumann, Oliver; Guirguis, Katharina; Steiner, Reto (2022): Exploring Artificial Intelligence Adoption in Public Organizations: A Comparative Case Study. In: Public Management Review 26 (1), pp. 114–141. DOI: 10.1080/14719037.2022.2048685.

Omrani, Nessrine; Rivieccio, Giorgia; Fiore, Ugo; Schiavone, Francesco; Agreda, Sergio Garcia (2022): To Trust or Not to Trust? An Assessment of Trust in AI-based Systems: Concerns, Ethics and Contexts. In: Technological Forecasting and Social Change 181, p. 121763. DOI: 10.1016/j.techfore.2022.121763.

Park, Hyanghee; Ahn, Daehwan; Hosanagar, Kartik; Lee, Joonhwan (2021): Human-AI Interaction in Human Resource Management: Understanding Why Employees Resist Algorithmic Evaluation at Workplaces and How to Mitigate Burdens. In: Kitamura, Yoshifumi; Quigley, Aaron; Isbister, Katherine; Igarashi, Takeo; Bjørn, Pernille; Drucker, Steven (Eds.): CHI 2021 Conference on Human Factors in Computing Systems Proceedings. New York, New York: ACM, pp. 1–15.

Prikshat, Verma; Islam, Mohammad; Patel, Parth; Malik, Ashish; Budhwar; Pawan; Gupta, Suraksha (2023a): AI-Augmented HRM: Literature Review and a Proposed Multilevel Framework for Future Research. In: Technological Forecasting and Social Change 193, p. 122645. DOI: 10.1016/j.techfore.2023.122645.

Prikshat, Verma; Malik, Ashish; Budhwar, Pawan (2023b): AI-Augmented HRM: Antecedents, Assimilation and Multilevel Consequences. In: Human Resource Management Review 33 (1), p. 100860. DOI: 10.1016/j.hrmr.2021.100860.

Pumplun, Luisa; Tauchert, Christoph; Heidt, Margareta (2019): A New Organizational Chassis for Artificial Intelligence – Exploring Organizational Readiness Factors. In: ECIS 2019 Proceedings. Stockholm, Uppsala: Association for Information Systems. Available online at: https://aisel.aisnet.org/ecis2019_rp/106 (retrieved on July 7, 2025).

Reich, Taly; Kaju, Alex; Maglio, Sam J. (2023): How to Overcome Algorithm Aversion: Learning from Mistakes. In: Journal of Consumer Psychology 33 (2), pp. 285–302. DOI: 10.1002/jcpy.1313.

Remneland Wikhamn, Björn; Styhre, Alexander; Wikhamn, Wajda (2023): HRM Work and Open Innovation: Evidence from a Case study. In: The International Journal of Human Resource Management 34 (10), pp. 1940–1972. DOI: 10.1080/09585192.2022.2054285.

Rogers, Everett M. (2003): Diffusion of Innovations. 5. Edition. New York, London, Toronto, Sydney: Free Press (Social Science).

Schmidt, Philipp; Biessmann, Felix; Teubner, Timm (2020): Transparency and Trust in Artificial Intelligence Systems. In: Journal of Decision Systems 29 (4), pp. 260–278. DOI: 10.1080/12460125.2020.1819094.

Schuessler, Elke S.; Lohmeyer, Nora; Ashwin, Sarah (2023): “We Can’t Compete on Human Rights”: Creating Market-Protected Spaces to Institutionalize the Emerging Logic of Responsible Management. In: Academy of Management Journal 66 (4), pp. 1071–1101. DOI: 10.5465/amj.2020.1614.

Tursunbayeva, Aizhan; Pagliari, Claudia; Di Lauro, Stefano; Antonelli, Gilda (2022): The Ethics of People Analytics: Risks, Opportunities and Recommendations. In: Personnel Review 51 (3), pp. 900–921. DOI: 10.1108/PR-12-2019-0680.

Vargas, Roslyn (2016): Adoption Factors Impacting Human Resource Analytics among Human Resource Professionals. Dissertation. Nova Southeastern University. Ann Arbor, Michigan: ProQuest Information & Learning.

Vargas, Roslyn; Yurova, Yuliya V.; Ruppel, Cynthia P.; Tworoger, Leslie C.; Greenwood, Regina (2018): Individual Adoption of HR Analytics: A Fine Grained View of the Early Stages Leading to Adoption. In: The International Journal of Human Resource Management 29 (22), pp. 3046–3067. DOI: 10.1080/09585192.2018.1446181.

Venkatesh, Viswanath; Morris, Michael G.; Davis, Gordon B.; Davis, Fred D. (2003): User Acceptance of Information Technology: Toward a Unified View. In: MIS Quarterly 27 (3), pp. 425–478. DOI: 10.2307/30036540.

4 Turning the Tide: Typologies of Temporary Managers in HR Decision-Making During Crises

4.1 Publication Details

Abstract:

In an increasingly volatile and uncertain business environment, organisations are turning to temporary managers, often referred to as interim managers, with greater frequency to navigate periods of crisis and transformation. Moreover, the successful management of crises is closely associated with skilful human resources (HR) decisions, which are characterised as uniquely complex, sensitive and simultaneously impactful. By virtue of their external status and limited tenure, temporary managers can make impartial and sometimes radical HR decisions without the burden of long-term internal consequences. However, they also face specific challenges, particularly in establishing authority and legitimacy within the organisation. This study explores the human capital that temporary managers contribute in crisis contexts, with a particular focus on their daily tasks, decision-making processes, and competency profiles. Drawing on a qualitative research design involving in-depth interviews with seventeen temporary managers, the analysis identifies three distinct typologies: *The Decider*, *The Advisor*, and *The Realiser*. These typologies reflect differentiated strategic orientations and align with Henry Mintzberg's framework for managerial roles. Thus, this study sheds light on the various strategic approaches that temporary managers employ to restore an organisation's profitability during crises, contributing to a broader understanding of the human capital that managers bring to organisations. Moreover, the findings extend Mintzberg's framework by incorporating human capital dimensions – namely, task structure, decision logic, and competence – into the role conceptualisation of temporary managers.

Co-Authors: Laura Jane Packheiser

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4.2 Introduction

In light of recent economic uncertainty, supply chain issues, high inflation rates, and geopolitical tensions, companies are facing increasingly comprehensive and complex challenges. In response to these challenges posed by the crisis environment, affected companies often seek external knowledge and expertise to support their crisis management efforts (Rosenthal and Hart 1991; Jibril et al. 2023). A common choice is to hire professional temporary managers who are contracted for a defined period to address uncertainty, manage various types of corporate crises, and, in the most critical scenarios, execute organisational turnarounds (Bruns and Kabst 2005; Woods et al. 2020). This is further compounded by the increasing practical importance of temporary managers in recent years. One notable indicator is the market for interim management in Europe, which has experienced significant growth in recent years, increasing by 14% over the past four years (Selby 2021; Selby 2024).

Depending on its severity, a crisis can yield profound consequences for organisations and their employees. From the company's perspective, crises may jeopardise the very survival of the business (Milburn et al. 1983). It places a heavy burden on the organisation's financial, physical, and emotional structures (Pearson and Mitroff 1993). Among employees, for example, research has shown that the perception of job-related uncertainty during corporate instability can evoke negative emotions, such as anxiety and frustration, ultimately leading to job disengagement (Ruppel et al. 2022). According to Kranz and Steger (2013), corporate crises lead to more centralised decision-making and reduced employee participation.

In theory and practice, the successful resolution of crises is closely tied to skilled human resource (HR) decisions. As early as 1987, Whitney named employees the '*make-or-break*' factor in corporate turnarounds (Whitney 1987). Thoughtful and proactive HR decisions are fundamental to overcoming immediate challenges, supporting employees, and positioning the company for long-term resilience and sustainable performance during and after a crisis. Malik and Sanders (2021) suggest that organisational Human Resource Management (HRM) and strategic decisions can have an impact on managing people during global crises, while Edvardsson and Durst (2021) report that HRM reacts in times of crisis with a wide range of different HRM practices, e.g. ranging from reduction in training, increasing outsourcing or job enlargement.

Temporary managers offer several advantages to organisations. They approach situations with an unbiased perspective, can make radical HR decisions without being constrained by internal political considerations, and can fully dedicate themselves to achieving organisational goals without the distraction of personal career interests within the company (Farquhar 1995). At the same time, they face unique ‘*on-the-job*’ challenges, such as gaining authority, acting under time pressure, and communicating contract status and contract duration (Flatøy 2024).

Despite their increasing deployment in crises, there remains a limited understanding of the specific human capital that these temporary executives bring to organisations. Mooney et al. (2017) emphasise the need for further research in this area. To address this gap, we focus on externally hired, temporary executives as key actors in decision-making during times of corporate distress.

Given both their unique advantages and the challenges they encounter, it remains unclear how temporary managers make decisions, what their daily tasks entail, and which competencies they leverage to guide organisations through crisis situations sustainably. This study aims to advance the current body of literature by examining these aspects in the context of HR decision-making, which becomes particularly critical in crises characterised by greater complexity, urgency, and reduced routinisation (Mulder et al. 1971). Accordingly, we pose the following research questions:

> **RQ1:** How do temporary managers apply and mobilise their human capital in navigating HR decision-making in times of crisis?

Understanding these parts of the human capital is a necessary foundation for exploring the role profiles that temporary managers adopt in such crisis environments. In these contexts, managers operate under ambiguous expectations and must adapt dynamically to the organisation’s needs. Thus, it is to be expected that different role profiles emerge that go beyond the traditional categories of managers and are characterised by their individual competencies and decision-making approaches. Identifying and understanding these role profiles enables a more nuanced understanding of how temporary managers contribute to organisational recovery – not only *what* they do but also *how* they enact their roles. We therefore ask:

> **RQ2:** Which distinct role profiles emerge among temporary managers navigating HR decision-making in times of crisis?

The daily tasks, HR decision-making processes, and competence profiles were identified by conducting qualitative, semi-structured interviews with experienced temporary managers from multiple countries. Furthermore, the interviews explored the managers’ selfperceived role orientations, drawing specifically on Mintzberg's managerial role framework (1973; 1975) to guide this inquiry. Seventeen interviews were conducted in Europe between the autumn of 2024 and the spring of 2025. In the first step, the interview data were manually transcribed and inductively analysed. In the second step, Mintzberg's management role framework was applied to categorise the findings.

Our study provides a twofold contribution to the literature. On the one hand, this study contributes to addressing the research call by Mooney et al. (2017) to examine in detail the specific human capital that different temporary managers might bring to an organisation. Thus, this study sheds light on the different strategic approaches that temporary managers apply in context to HR decisions in crises, focusing on how they operate in practice and the capabilities they bring to bear. Based on these insights, three typologies of temporary managers – *The Decider, The Advisor,* and *The Realiser* – can be distinguished.

On the other hand, Mintzberg's framework of managerial roles (1973; 1975) is enriched by expanding the perceived role profiles of temporary managers to include the associated human capital, namely their daily tasks, decision-making processes and competency profiles. This represents a transfer and categorisation of the interpersonal, informational, and decisional roles of temporary managers, expanding Mintzberg's managerial role framework to include human capital.

Our paper is organised as follows. In the next section, we present the current state of the literature on the theoretical background of our study, highlighting the research questions that guide our investigation. In addition, we present the underlying framework, namely Mintzberg's framework of managerial roles (1973; 1975). Section 3 explains the method and analytical steps used. The following sections present (section 4) and discuss (section 5) our results. We conclude with reflections on the limitations of our study and potential avenues for future research.

4.3 Literature Review

4.3.1 Human Resources Decisions in Crises

Globalisation and the accelerated pace of digitalisation within a volatile economic environment have significantly shaped the modern corporate landscape. Consequently, many organisations experience periods of substantial performance decline at some stage of their life cycle, necessitating strategies to address the resulting challenges (Hofer 1980; Miller and Friesen 1984; Pretorius 2008; Trahms et al. 2013; Bundy et al. 2017; Gotteiner et al. 2019). Thus, the challenges associated with business rescue and crisis management in distressed companies are well-established topics in academic discourse (e.g. Barker and Mone 1994; Smith and Graves 2005; Liou and Smith 2007; Gotteiner et al. 2019). The phenomenon of corporate decline and turnaround has been studied in management research for several decades, introducing broad conceptual frameworks that still form the basis of turnaround research today (Altman 1968; Gordon 1971; Schendel and Patton 1976; Hofer 1980; Hambrick and Schecter 1983; Schoenberger et al. 2013).

New management practices have evolved in recent years to address organisational challenges. Empirical research on these practices has demonstrated their effectiveness in facilitating business recovery, commonly referred to as turnaround strategies (O'Shaughnessy 1986; Grinyer et al. 1990; Schoenberg et al. 2013; Gotteiner et al. 2019). Turnaround management is conceptualised as a multifaceted process to revitalise organisations experiencing crises. This process entails rescuing and recovering struggling entities by effectively utilising analytical frameworks and planning methodologies. Due to the numerous factors contributing to organisational decline, the increasing frequency of corporate insolvencies, and the adverse global economic conditions, a considerable body of research has investigated both successful and unsuccessful efforts in organisational turnaround (e.g. O'Neill 1986; Balgobin and Pandit 2001; Smith and Graves 2005; Liou and Smith 2007; Bruton et al. 2010; Gotteiner et al. 2019). Even when a situation does not escalate to a full-scale turnaround, decisions related to human resources (HR) remain an important aspect of effectively managing organisational challenges (Trunk and Birkel 2022). As Kim et al. (2013) demonstrate, companies with poor prior performance tend to adopt new HRM systems to improve their performance. Consistent with the resource-based view, research by Holcomb et al. (2009) emphasises the importance of HR decisions by showing that management decisions in the HR department impact the overall value-creation process of the company. Their results suggest that managerial ability and actions affect resource productivity, but their influence is moderated by the quality of the organisation's human resources (Holcomb et al. 2009). Förster et al. (2022) highlight that successfully navigating a crisis demands leaders to adjust not only their actions but also their mindsets (Lewis and Smith 2022) – a dual challenge that underscores the complexity of leadership in times of crisis.

The following section provides an overview of the current literature on the HR decisions of temporary managers, including their advantages and challenges.

4.3.2 Temporary Managers (Facing HR Decisions)

Current research indicates that most corporate failures are due to poor or inappropriate management practices (Ahn et al. 2000; Dubrovski 2009; Zambrano Farias et al. 2021), with estimates suggesting that around 80% of failures are due to management incompetence (Scherrer 2003). The challenges managers face during an organisational turnaround differ from those encountered when improving performance in a stable environment (Carmeli and Sheaffer 2009; Trahms et al. 2013). In this context, Boyne and Meier (2009) argue that appointing professional executives to temporarily take charge of an organisation and bridge a management function is more effective for turnarounds than relying solely on external consultants. Their findings suggest that insiders, with their contextual expertise, are more likely to implement successful survival strategies than outsiders (Boyne and Meier 2009; Bronnenmayer et al. 2016). In management research, Smid et al. (2006) also emphasise the role of temporary managers in facilitating organisational change processes.

Different labels are used for externally and temporarily contracted professional executives in literature and practice. For example, the terms *Temporary Leaders* (e.g. Farquhar 1995; Browning and McNamee 2012; Bae et al. 2021), *Interim Managers* (e.g. Goss and Bridson 1998; Inkson et al. 2001; Jas 2013; Flatøy 2024), *Interim CEOs* (e.g. Ballinger and Marcel 2010; Intintoli et al. 2014; Mooney et al. 2017; Bae et al. 2022) or *Interim Leaders* (e.g. Woods et al. 2020; Fisher et al. 2024) are frequently used. The various authors agree on the characteristics of temporary managers and offer congruent definition criteria. Inkson et al. (2001) provide a comprehensive definition, describing the profession as "*a management professional, usually with a specific area of expertise, who contracts, often through an agency, to provide a client company with short-term cover, troubleshooting in an area of expertise, or completion of a pre-defined project*" (Inkson 2001, p. 260), while Goss and Bridson (1998) particularly emphasise that interim managers are explicitly limited to temporary and short-term bases. Woods et al. (2020) highlight the functional level, as the temporary executives "*may also be defined in terms of what they do; interim management is the management of the transition, change, uncertainty or crisis by a suitably overqualified executive, commissioned at a senior level on an assignment basis*" (Woods et al. 2020, p. 174–175), studies generally neglect the areas in which interim managers are appointed.

We argue that HR decisions are especially critical in times of crisis or turnaround while being characterised as uniquely complex, sensitive and impactful at the same time

(Mulder et al. 1971). We therefore concentrate on this field of application for temporary managers. There are some more general studies with contributions in the context of HR and temporary management. Goss and Bridson (1998) focused on the place of interim management in the HR strategy and raised questions about, for example, the best way to evaluate interim success. The review by Woods et al. (2020) analyses interim leaders from an HR perspective to further understand interim assignment performance and the antecedent individual psychological characteristics. Flatøy (2024) finds evidence that acting quickly, gaining authority, and communicating contract status and contract duration are the most significant '*on-the-job*' challenges for interim executives. The research landscape has so far not addressed the human capital associated with temporary managers (Mooney et al. 2017), specifically their daily tasks, decision-making processes, and competence profiles.

Mintzberg's framework of managerial roles (1973; 1975) is used to anchor the research results theoretically. The framework is therefore presented in the following paragraph.

4.3.3 Mintzberg's Theoretical Framework

Mintzberg's framework of managerial roles (1973; 1975) provides a comprehensive lens through which managers' multifaceted responsibilities and activities in their daily business can be understood. Although there has been criticism of the work of Mintzberg (e.g. Snyder and Wheelen 1981; Martinko and Gardner 1985), his findings have been replicated by other researchers (Kurke and Aldrich 1983), while most of Mintzberg's propositions are still valid (Tengblad 2006) and still used in today's literature (e.g. Dandalt 2021; Labaronne and Müller 2024). Mintzberg's ten roles, categorised into interpersonal, informational, and decisional dimensions, offer insights into the broad and dynamic nature of management. He does not limit his work to CEOs but emphasises that it applies to all other individuals who "*are vested with formal authority over an organisational unit*" (Mintzberg 1975, p. 54). The formal authority is built on status, leading to several interpersonal relations. These provide access to information that allows decisions to be made within the scope of one's decision-making powers (Mintzberg 1975).

Mintzberg's interpersonal dimension includes *Figurehead*, *Leader* and *Liaison* to emphasise the relationships managers must foster, both within and outside the organisation, and are critical for establishing authority, influence, and collaboration. Ceremonial and symbolic tasks arising from the manager position are bundled into the role of Figurehead. As a Leader, the manager is responsible for hiring, training, and motivating employees while balancing their individual needs with the organisation's goals. In his work, Mintzberg complements the Liaison role, in addition to their '*vertical chain of command*' (Mintzberg 1975, p. 55), by building their external information system and fostering relationships across different units or with external stakeholders (Mintzberg 1973; Mintzberg 1975).

The informational dimension underscores the manager's role in gathering, processing, and disseminating knowledge to ensure informed decision-making. The framework includes three informational roles: *Monitor*, *Disseminator* and *Spokesperson*. While the dimension of a Monitor represents the constant collection of information, the role of a Disseminator illustrates the forwarding and moderation of information within the workforce. In contrast, as a spokesperson, the manager sends information to other higher hierarchies or outside the organisation (Mintzberg 1973; Mintzberg 1975).

The decisional dimension captures the essence of a manager's authority and responsibility in steering the organisation's direction and addressing challenges. Four decisional roles emerge: The *Entrepreneur*, *Disturbance Handler*, *Resource Allocator* and *Negotiator*. As an Entrepreneur, the manager acts as an initiator of change and aims to improve their unit proactively. In contrast, as a Disturbance Handler, the manager responds to involuntary pressure, such as unforeseen crises or conflicts. The decision on how resources are distributed across projects or units, as well as the authorisation of decisions, lies in the role of a Resource Allocator. The role of the Negotiator presents the authority to negotiate on behalf of the organisation, whether it involves contracts, resource sharing, or conflict resolution (Mintzberg 1973; Mintzberg 1975).

Mintzberg (1975) suggests remembering that the dimensions and roles are inseparable and form an integrated whole. Nevertheless, managers force the roles differently (Mintzberg 1975; Shapira and Dunbar 1980). As temporary managers have unique characteristics, like the need to adapt quickly to new, often crisis-inflicted environments, this field provides significant opportunities to understand how Mintzberg's interpersonal, informational, and decision-making roles manifest themselves during a temporary assignment. The study offers an opportunity to gain a deeper understanding of the role profiles of temporary managers, as these can be compared with evidence on decision-making processes, daily tasks, and characteristics.

4.4 Methodology

A qualitative research design was selected due to its potential to generate in-depth insights into the everyday activities and decision-making processes of temporary executives, thereby enabling a nuanced understanding of their professional practices and the contextual conditions under which they operate. This approach aligns with the exploratory nature of the study, which seeks to develop new theoretical perspectives (Wickert and De Bakker 2018). In this context, interviews are the most appropriate method for capturing the complexity of the research subject and addressing the research questions comprehensively (Patton 2015). Building on previous interpretive studies, the in-depth interviews were conducted in a semi-structured format to facilitate the emergence of sense-making narratives (e.g. Brown et al. 2008) while allowing for the collection of diverse information, including personal perspectives and experiences. Additionally, critical incident questions, focused on specific events and occurrences, were incorporated to anchor the discussions in the lived experiences of temporary managers (see Flanagan 1954).

The guideline that facilitated our interviews was constructed around the literature review and in accordance with our research questions. The questionnaire was pre-tested on researchers and practitioners and comprised queries in the following areas: concepts and organisations, decision-making process, role perception, skills, and the impact of digitalisation. While the sequence of questions was occasionally adjusted during the interviews to accommodate the flow of conversation, and the interview guide was refined throughout the research process to incorporate emerging empirical insights, it nevertheless ensured the collection of a comparable and consistent dataset across all interviews. The interviews were supplemented with follow-up questions to enhance the depth of the chosen research approach. Consistent with the research strategy, open-ended questions were employed to facilitate adaptability to each interviewee's expertise and experiences (Ditillo 2004).

To facilitate an examination of the functions performed by experienced temporary managers, a purposive sampling strategy was employed to identify interim managers actively engaged in HR decision-making during organisational crises. In this study, interim managers are conceptualised and operationalised as representative examples of temporary executives. The managers were recruited through targeted outreach via professional associations, snowball sampling, LinkedIn, and direct contact. The study employed a purposive sampling strategy where participants were selected based on predefined characteristics and criteria relevant to the research objectives. The primary objective in selecting the interview sample was to ensure diversity among temporary managers from various European countries, thereby enabling the study to capture insights beyond localised contexts, such as legal conditions or differences in local corporate structures. The interviewees contributed diverse professional backgrounds, having acquired experience across organisations of varying sizes and spanning multiple sectors of the economy. Table 14 details the participant's professional characteristics, including their official job title, their experience, and information about their mandates.

Table 14: Study participant characteristics

Official job title / number of interviewees	General Interim Manager: 5 HR Interim Manager: 6 Interim CRO/CEO: 6
Interviewees' genders	Female: 2 Male: 15
Country	Germany: 5 UK: 3 Netherlands: 2 Austria: 2 Romania: 1 Sweden: 1 France: 1 Italy: 1 Swiss:1
Years of experience	Average: 15 years Q1: 7 years Q3: 20 years
Number of mandates	Total: 945 Average: 55 Q1: 5 Q3: 30
Duration of mandates	Average: 17 months Shortest: 3 months Longest: 60 months
Company sizes	Average: 1.200 employees Q1: 100 employees Q3: 1.200 employees

The data collection consisted of seventeen narrative interviews with interim managers who faced HR decisions in crisis situations. Our empirical study focuses exclusively on mandates that are confronted with crises that threaten their existence. We conducted the interviews collaboratively between October 2024 and March 2025 in English or German. One author facilitated the interviews, while the other systematically documented observational notes. Interview durations ranged from 28 to 70 minutes, averaging approximately 53 minutes, resulting in a total of around 15 hours of dialogue. All interviews were audio-recorded and transcribed afterwards. Finally, the number of interviews was determined inductively, i.e. the data collection was terminated when no new findings and patterns relevant to the research questions emerged, which corresponds to the principles of theoretical saturation (Lincoln and Guba 1985; Glaser and Strauss 2009; Gioia et al. 2012, p. 20).

The data analysis follows Gioia's methodology (Gioia et al. 2012), in which the codes, after being assigned to the categories, are first summarised in superordinate themes and theories (first-order analysis) (Van Maanen 1979; Gioia et al. 2012; Wickert and De Bakker 2018) and then aggregated into dimensions to be able to generate hypotheses in the further course (second-order analysis). The coding grid was jointly developed by the research team and validated collectively. Coding was performed with MAXQDA software (version 2024). The results presented in this article were illuminated by representative interview statements intended to allow the reader a deep understanding of the situations described and thoughts presented (Patton 2015). To protect anonymity, we removed all identifying information from the text (e.g. names of interviewees, firms, and places).

Early impressions during the interview phase indicated the presence of three differentiated typologies of temporary managers. Through an iterative analysis of the empirical data in conjunction with the relevant literature, distinct patterns emerged, enabling us to assign appropriate theoretical labels to the identified characteristics and thus distinguish among three groups. Based on the identified second-order themes, distinct patterns emerged across the sample, allowing for a nuanced differentiation of temporary managers along multiple dimensions. This analytical approach allowed us to move beyond aggregated categories and uncover underlying linkages among the participants, ultimately facilitating the development of three typologies of temporary executives: *The Decider*, *The Advisor*, and *The Realiser*. These typologies capture divergent HR decision-making processes, daily tasks, competence profiles, as well as managerial roles, and provide a structured understanding of the human capital that temporary managers contribute during crises.

4.5 Results

The results address both research questions jointly by integrating empirical findings with relevant theoretical perspectives. Figure 13 illustrates the data structure and key attributes distinguishing the three types, while Table 15 links these typologies to Mintzberg's (1973; 1975) managerial role framework. The observed commonalities and divergences not only enrich our understanding of the strategic orientations of temporary managers but also contribute to the theoretical integration of these role profiles within broader management and organisational research.

The following section provides a detailed account of each typology, outlining their defining characteristics and contextual relevance.

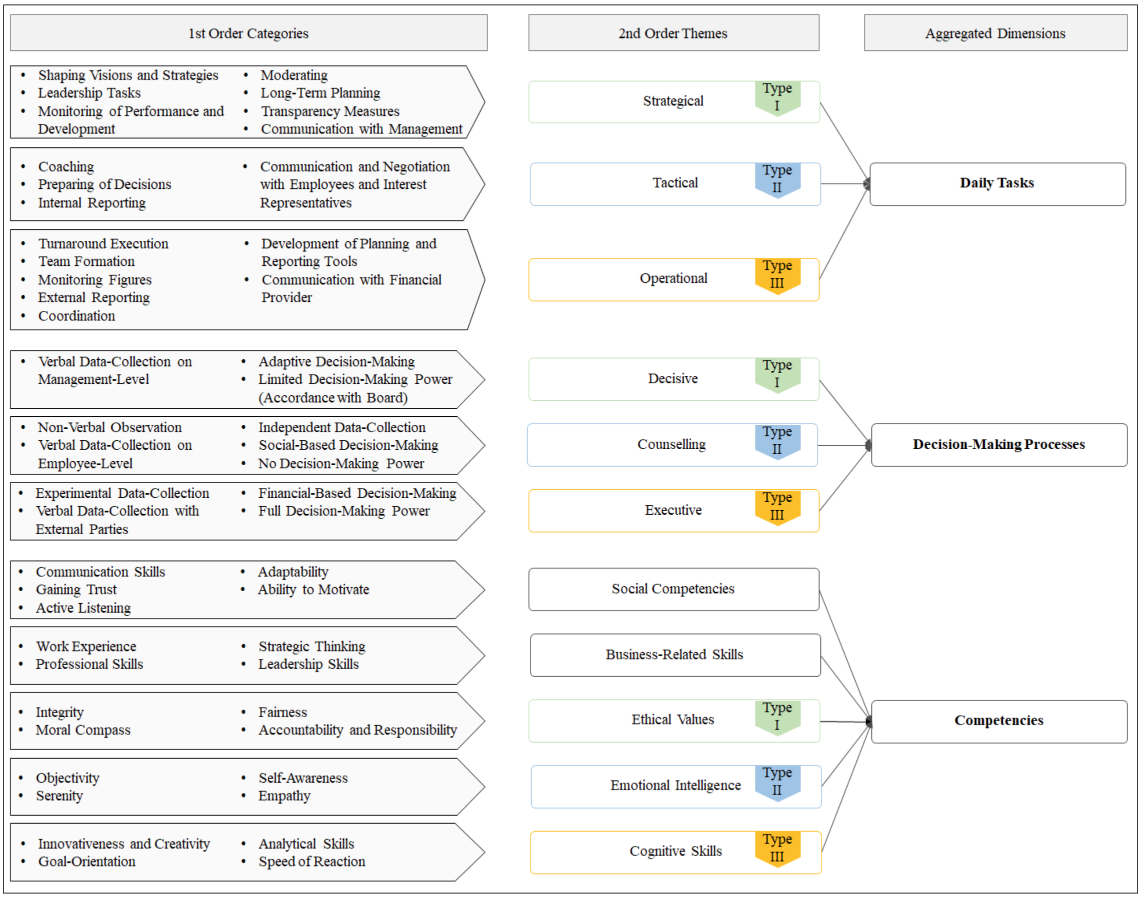

Figure 13: Data structure (first-order categories summarised by key topic and key attributes of the three temporary manager typologies)

Table 15: Characteristics of the three typologies of temporary managers

	Typ I	**Typ II**	**Typ III**
Daily Tasks	Strategical	Tactical	Operational
Decision-Making Processes	Decisive	Counselling	Executive
Overall Competencies	Social Competencies, Business-Related Competencies		
Special Competencies	Ethical Values	Emotional Intelligence	Cognitive Skills
Primary Interpersonal Management Roles	Leader	Liaison	Figurehead
Primary Informational Management Roles	Disseminator	Monitor	Spokesperson
Primary Decisional Management Roles	Entrepreneur & Disturbance Handler	Negotiator & Disturbance Handler	Negotiator & Resource Allocator
	The Decider	***The Advisor***	***The Realiser***

4.5.1 The Decider

Type I, referred to as *The Decider* (n = 5), reflects a distinct and analytically robust pattern within the behavioural spectrum of temporary executive behaviour. This typology is characterised by a pronounced orientation toward strategic transformation, decisive action-taking, and a firmly anchored value system. Emerging from the empirical analysis of second-order themes, *The Decider* exemplifies a category of temporary executives who assume responsibility not merely for operational continuity but for the formulation and execution of long-term strategic trajectories. Within the framework of temporary leadership, where time constraints, high complexity, and performance pressure converge, this type of temporary manager plays a pivotal role in navigating organisations through ambiguity toward strategic clarity.

At the core of this typology lies a deeply embedded strategic orientation. *The Decider* operates on a metalevel, engaging in activities that define and shape the organisation's future position. This involves vision setting, environmental scanning, scenario planning, and prioritising transformational agendas. Their daily tasks reflect a high degree of abstraction and integrative thinking, enabling them to align short-term interventions with long-term organisational viability. These behavioural patterns are consistent with research on strategic sensemaking (Gioia and Chittipeddi 1991) and executive foresight (Rohrbeck and Kum 2018), which emphasise the cognitive ability of leaders to frame emerging challenges, anticipate inflection points, and mobilise strategic responses under uncertainty.

Complementing this forward-looking mindset is the theme of *decisiveness*, which serves as a behavioural anchor in *The Decider's* leadership repertoire. This type consistently demonstrates the ability to make high-stakes decisions under time pressure and with limited information, a condition often inherent in interim contexts. Rather than relying on participatory or consensus-driven processes, *The Decider* adopts a directive, outcome-focused approach to decision-making. Drawing on targeted verbal inputs gathered through top-level interactions and rapid assessments, these leaders quickly and clearly translate insights into action. This decision-making logic aligns with *Models of Bounded Rationality* (Simon 1955) and *Strategic Agency* (Child 1997), which emphasise action orientation, risk management, and assertive governance. In transitional environments, where ambiguity and urgency are salient, such a capacity for fast and authoritative decision-making becomes a core source of executive effectiveness.

Further differentiating this type is its grounding in *ethical values*. Across cases, *The Decider* exhibits a coherent moral compass marked by integrity, responsibility, and principled judgment. These leaders act in accordance with deeply held normative standards, which guide their interactions and serve as an internalised framework for evaluating strategic options, especially when making HR decisions. In many instances, these ethical convictions are not explicitly communicated but embedded in their leadership demeanour and decision rationales. Such a value system becomes particularly relevant in contexts where organisational legitimacy is fragile – such as during turnarounds, cultural realignments, or crisis recovery phases. This orientation underscores the importance of ethical consistency in stabilising organisations and enhancing leader credibility during change processes.

While all temporary executives must possess a baseline of managerial and interpersonal competencies, what distinguishes *The Decider* is the synthesis of strategic foresight, decisive execution, and ethical anchoring into a coherent leadership profile. These individuals are not merely transitional placeholders; instead, they function as transformative agents who reorient organisations toward long-term viability. They contribute to providing direction at moments of strategic drift, making consequential decisions where others hesitate, and upholding principles that foster trust and alignment.

Viewed through the lens of Mintzberg's (1973; 1975) managerial role framework, *The Decider* activates a specific configuration of roles. Interpersonally, they function as Leaders, providing direction, motivation, and symbolic guidance to top-level stakeholders and transitional teams. Informationally, they assume the role of Disseminators, selectively filtering and communicating relevant strategic insights within the organisation. Decisively, they embody the roles of both Entrepreneurs by initiating change and driving innovation and Disturbance Handlers by resolving crises and recalibrating organisational trajectories under duress. This role enactment highlights the multifaceted nature of temporary executive leadership, where strategic, communicative, and corrective actions are tightly interwoven to restore and secure organisational viability.

In conclusion, *The Decider* constitutes a central figure in temporary executive leadership. Their effectiveness stems not only from *what* they do but also from *how* they do it – with strategic clarity, moral integrity, and a capacity for decisive leadership. This typology captures the essence of a temporary executive who assumes responsibility in moments of uncertainty and delivers impact through principled and future-oriented action.

4.5.2 The Advisor

Type II, referred to as *The Advisor* (n = 7), represents a typology of temporary executives whose leadership is marked by consultative engagement, contextual sensitivity, and a relationally grounded influence style. Unlike leaders who aim to impose strategic overhauls, *The Advisor* operates primarily as a facilitator of reflection and organisational learning. Within the volatile context of interim leadership, defined by temporary mandates, ambiguous authority structures, and rapidly shifting expectations, this type provides value not through formalised decision power but through enabling others to act with greater clarity and competence. Their role is situated within a framework of temporary authority that demands both humility and influence without control (Sturdy 2011).

At the core of *The Advisor'*s leadership profile lies a commitment to tactical support and participative development. Rather than prioritising high-level strategic realignment, this type focuses on operational-level guidance and mid-term decision support. This includes team coaching, informal consultations, and structured feedback loops to empower line managers, especially when it comes to significant HR decisions. These practices align with process consultation frameworks (Schein 1999), where the emphasis is not on delivering solutions but on enhancing the client system's capacity to diagnose and address its challenges. *The Advisor'*s interventions often unfold through reflective questioning, reframing, and perspective-taking, promoting organisational learning in real-time.

A defining behavioural theme of this typology is relational influence without formal authority. This implies that *The Advisor* must rapidly establish credibility and psychological safety, often in politically sensitive or emotionally charged contexts. Their effectiveness depends on their ability to build trust-based relationships and act as a neutral third party, enabling candid conversations and lowering organisational defensiveness. This aligns closely with the literature on *Emotional Intelligence in Leadership* (Goleman 1998), as well as with *Theories of Sense-Giving* (Gioia and Chittipeddi 1991), where leaders help shape the meaning-making processes of others without asserting dominance over outcomes.

While *The Advisor* tends to refrain from high-stakes decision-making, they contribute to ethical alignment and organisational cohesion by reinforcing consistency, fairness, and empathetic engagement. Their moral compass is often enacted less through overt ethical declarations and more through subtle behavioural cues, such as respectful listening, inclusive dialogue, and interpersonal transparency. These patterns resonate with servant leadership principles (Eva et al. 2019), wherein the leader's primary aim is to elevate others' capabilities and foster a morally grounded environment for decision-making.

When interpreted through the lens of Mintzberg's (1973; 1975) managerial roles, *The Advisor* demonstrates a distinctive profile. On the interpersonal level, they operate as Coordinators, shaping their influence through emotional attentiveness, informal authority, and developmental support. By mentoring others and modelling calm under pressure, they foster trust and cohesion in times of uncertainty. Regarding information processing, they adopt the role of Monitor, attentively observing the organisational climate and interpersonal dynamics. Their strength is detecting subtle signals, emerging tensions, unspoken concerns, or evolving needs before they escalate or crystallise into barriers. This vigilance equips them with a nuanced understanding of the context, enabling them to provide proactive guidance. In decision-making, *The Advisor* primarily serves as a Negotiator, engaging in ongoing, internal dialogue to align diverse interests, broker understanding, and resolve conflicts. Their focus lies within the organisation, using tactful communication to build consensus and ensure stability during the transition. Additionally, they exhibit traits of a Disturbance Handler, stepping in when disruptions arise to de-escalate tensions and guide collaborative resolution. These roles define *The Advisor* as an integrative force – supporting adaptive progress through relational leadership and contextual awareness.

In sum, *The Advisor* reflects a type of temporary executive whose value lies in their ability to embed themselves relationally, empower internal actors, and serve as a mirror for the organisation's latent potential. Their contribution is inherently subtle but powerful – providing reflective space, ethical consistency, and an empathetic presence in the midst of uncertainty.

4.5.3 The Realiser

Type III, referred to as *The Realiser* (n = 5), represents a third and distinct pattern of temporary executive behaviour, mainly characterised by a strong implementation focus, pragmatic orientation, and a pronounced sense of operational ownership. While other typologies in our study emphasise strategic vision or cognitive facilitation, *The Realiser* is grounded in executional rigour and action orientation. This typology emerged from second-order themes such as hands-on implementation, accountability for outcomes, and tactical alignment, pointing to a leadership style focused on translating plans into tangible organisational results.

Central to *The Realiser*'s identity is the ability to quickly absorb complex operational contexts and convert them into executable processes. This manager type is typically brought in when strategic plans have already been developed or are externally provided – and the organisational challenge lies in realising them under time pressure and resource constraints. *The Realiser* thrives in these high-demand, often turnaround-type environments where clarity of direction must be combined with speed, accuracy, and performance monitoring. In this regard, *The Realiser* aligns closely with what Huy (2001) describes as emotional balancing agents – leaders who maintain stability while pushing implementation forward under conditions of organisational strain.

Another core characteristic is their deep anchoring in practical feasibility. Instead of abstract reflection or long-term modelling, *The Realiser* draws on a logic of practical problem-solving. Their leadership is shaped by what Schön (1983) called '*reflection-in-action*', meaning they continuously adapt their methods and interventions in real-time as new constraints or data emerge. In contrast to *The Decider*'*s* top-down strategic orientation or *The Advisor*'s facilitative mode, *The Realiser* leads through close interaction with operational teams, active troubleshooting, and a visible presence in the execution layers of the organisation.

Decision-making for *The Realiser* follows an integrative yet non-theoretical path, relying on experiential knowledge, cross-functional coordination, and contextual prioritisation. This approach bears resemblance to the *Concept of Pragmatic Rationality* (Brunsson 1982), where the emphasis is on doing what works in the given organisational constraints rather than adhering to abstract models or principles. Accordingly, this typology often involves reconfiguring teams, adapting KPIs, and streamlining workflows, aiming to achieve measurable results rather than perfect strategic alignment.

Ethical behaviour remains relevant for *The Realiser*, albeit more implicit than in *The Decider*. Integrity manifests less through normative posturing and more through consistency in action, fairness in performance evaluation, and transparent communication with employees during the implementation phases. As such, *The Realiser* often earns trust through reliability and resilience, becoming an essential stabiliser in turbulent organisational conditions (Pinkwart et al. 2022).

In their interpersonal function, *The Realiser* assumes the role of Figurehead, lending symbolic weight and visible support to the execution process. Through routine presence and ceremonial functions, they legitimise the initiative and reinforce its priority within the organisational culture. When it comes to information flow, *The Realiser* steps into the role of Spokesperson, conveying structured updates and articulating implementation progress to internal and external stakeholders. Their communication ensures alignment, transparency, and sustained focus across the delivery timeline. Decisional responsibilities are anchored in the roles of Negotiator and Resource Allocator. As Negotiators, they manage competing demands and facilitate alignment among external stakeholders, often navigating operational trade-offs to maintain momentum. Simultaneously, they act as Resource Allocators, deploying personnel, budgets, and attention to where they are most needed to ensure timely and disciplined delivery. Together, these roles position *The Realiser* as the pragmatic core of transitional leadership: outcome-oriented, grounded, and indispensable in converting strategic intention into operational reality.

Table 16 provides a detailed overview of the quotation examples for the results.

Table 16: Dimensions, themes, categories, and representative quotations

Second-Order Themes and First -Order Categories	**Representative Quotations**
Aggregated Dimension: Daily Tasks	
1. Strategical	
A. Shaping Visions and Strategies	[You] work out what you've got to do to survive a bit longer. And then you start thinking about missions and goals and strategy and so on and so forth (I02, 144).
B. Leadership Tasks	The most important thing that I do when I arrive is to be a leader and I'm going to define leadership (I02, 112).
C. Monitoring of Performance and Development	You have to make notes during the year and monitor your progress (I12, 36).
D. Moderating	I am a catalyst and moderator. Or the independent external designer. (I01, 84).
E. Long-Term Planning	It's about proposing a long-term solution or working out a solution together with us (I16, 26).
F. Transparency Measures	F1. Transparency and explaining very open and, on their way of understanding what we want to say. So this is probably one of the first major efforts. To try to put it in their language (I04, 100).
	F2. What is important is the first thing that you have to explain very well to the people why you are there and what's the scope (I04, 96).
G. Communication with Management	G1. You start interviewing the management first, you start interviewing the second and the third line (I04, 80).
	G2. The most important thing is talking to the board or the CEO (I12, 70).
2. Tactital	
A. Coaching	A1. Basically, [I'm] really more of an internal coach for employees, rather than a traditional leader (I07, 77).
	A2. I would rather say I am your mentor or I coach you, I stand by your side, I come in with an entrepreneurial eye, but ultimately I still have to look at my role and distance myself (I08, 74).
B. Preparing of Decisions	B1. I don't make the decision by myself, I actually prepare it together with the management team (I05, 60).
	B2. You can provide basis for decision, arguments, recommendations, analysis, pros and cons, advantages and disadvantages, experience, examples, illustrations, but ultimately the decision stands with the leader or the figurehead or both (I09, 83).
C. Internal Reporting	This includes communication within the company, providing them with information and key figures (I08, 72).

Second-Order Themes and First -Order Categories	**Representative Quotations**
D. Communication and Negotiation with Employees and Interest Representatives	I always start by interviewing as many employees as possible, because you tend to find that the board doesn't actually give you the real story of what's going on. So particularly when you've got an operation that's people heavy, if you've got a lot of manufacturing or something like that, then I would get down on the factory floor and speak to as many people as possible (I15, 24).
3. Operational	
A. Turnaround Execution	A1. When you implement the action plan, after defining the main actions, you are always there to follow it, to be sure that everything goes the proper way while like a real captain on the ship (I10, 23).
	A2. It gets really exciting when you get into operational turnarounds and crisis processes (I14, 14).
B. Team Formation	I like to build a team around me [...] with the champion or whoever has an interest that this turnaround goes the proper way (I10, 78).
C. Monitoring Figures	You also monitor that the process and the KPIs and the information and everything goes the proper way and the action plan goes the proper way (I10, 70).
E. External Reporting	Later on, there is reporting for all these people, whether they are shareholders or banks or whoever gives money (I03, 60).
F. Coordination	My overriding principle as an interim manager is to coordinate from the background (I6, 78).
G. Development of Planning and Reporting Tools	I set up the management accounting. [...] The only way to do this, of course, is by making some kind of calculation and by looking at the business areas, segmenting the company and dividing it into service categories and then seeing which are profitable and which are not (I03, 46).
H. Communication with Financial Providers	Usually, we then also have the task of not only implementing these measures, but also discussing with the people who are financing these measures about what we are doing (I03, 60).
Aggregated Dimension: Decision-Making Processes	
1. Decisive	
A. Verbal Data Collection on Management-Level	The one-on-one meetings [with management] provide figures to secure the basis for my decision-making (I02, 64).
B. Adaptive Decision-Making	Everything that I can decide, I should decide. I adjust to the company. (I01, 52).
C. Limited Decision-Making Power	When it comes to issues, of course, then the consultation with the management, the restructuring issues are typically worked out in a larger team and then also decided together with the management (I01, 52).
2. Counselling	
A. Non-Verbal Observation	The dual verbal information is extremely important. People can manage their words, but people cannot manage their faces. And it's always very important to look to the faces of the people. What does this face say? And if you do that – during the day and during the week and how they work, how they walk around in your company, that gives a lot of information (I9, 64).
B. Verbal Data-Collection on Employee-Level	I usually talk for an hour with every employee, and it's around 30 employees, so then it takes up quite some time. And before I did the interviews super structured. I asked every employee the same question, which was good, but it was also very time consuming. So now I'm a bit more semi-structured, I have a couple of questions in my head, but I also give myself space to dive deeper into a topic when I feel that is an important topic for someone. But of course, that is an important part of where my time goes (I13, 38).
C. Independent Data-Collection	I simply have to identify not only official information but also informal and unofficial information (I11, 42).
D. Social-Based Decision-Making	I'm looking for reasonable social measures to soften the blow (I05, 156).
E. No Decision-Making Power	E1. For the companies I'm working with now I was not the final decision maker, but I was involved in the process (I13, 52).
	E2. At the end of the day, I, as an interim manager, am not the one who ultimately makes the decision (I07, 40).

Second-Order Themes and First -Order Categories	Representative Quotations
3. Executive	
A. Experimental Data-Collection	I told him that I would like to have a work uniform, and then I'm doing the night shift – and then he declared me crazy and then I told him to let me do it. And that was a really exciting story. I actually worked the night shift at the blast furnace and it was very hot and very rustic. But of course you get to talk to the people who are actually on the shop floor. That night, I got to know all the problems of this company first hand. And yes, then the turnaround concept was actually relatively clear, where it had to go (I14, 36).
B. Verbal Data-Collection with External Parties	If I have to talk to a supplier or a customer or a bank, I am of course a representative (I14, 70).
C. Financial-Based Decision-Making	My decisions are always linked to the financials of the company. So the understanding of the financials is essential to really have a clear picture of the expectations of this situation (I10, 25).
D. Full Decision-Making Power	D1. Usually the CEO doesn't have any control by the time I'm there (I17, 42).
	D2. That's why I value a lot of decision-making authority on my part (I14, 36).
Aggregated Dimension: Competencies	
1. Social Competencies	
A. Communication Skills	A1. For me, communication and how you deal with each other is a very, very important component of interim tasks (I03, 124).
	A2. So as long as you're true and honest in communicating why you're doing things, then it goes a lot better (I06, 130).
B. Gaining Trust	B1. I try to be worthy of people's trust because the bigger the trust zone that you can have between two people, the more work you can do (I02, 140).
	B2. You need to practically open the door, create your own way, and then start to message everything in such a way that you are winning their trust (I04, 96).
C. Active Listening	And that has to do with reading people, listening very well. Ask. Ask the good questions and keep your mouth and listen. That's extremely important (I12, 82).
D. Adaptability	To succeed you need to adapt. So change while being flexible enough (I10, 31).
E. Ability to Motivate	E1. Awaking their own motivation and giving them the purpose […] (I12, 52).
	E2. Motivate people to stay, because it is precisely in situations like this that many people leave and then key employees always leave too (I08, 31).
2. Business-Related Skills	
A. Work Experience	A1. Trusting your gut, which comes from experience, that's not something you can teach anybody (I15, 68).
	A2. Experience, life experience, and managerial experience have certain advantages (I11, 30).
B. Professional Skills	Without having to know what I'm doing from a professional point of view, there's no question about it. These are all basic requirements and skills that you have to have. Otherwise you can't do the job at all (I03, 124).
C. Strategic Thinking	We must be able to think long-term and find solutions for the future (I08, 31).
D. Leadership Skills	The most important thing that I do when I arrive is to be a leader and I'm going to define leadership (I02, 112).
3. Ethical Values	
A. Integrity	You need to lead a little bit by example. I mean, you cannot ask from people, efforts or understanding of things that you do not understand (I04, 164).
B. Moral Compass	You also need some ethical principles (I16, 48).
C. Fairness	You need to treat people politely and fairly and encourage people to understand that they're not useless. It's just a bad situation (I12, 60).
D. Accountability and Responsibility	It is practically your own decision. It's your own commitment and your own responsibility (I04, 128).

Second-Order Themes and First -Order Categories	**Representative Quotations**
4. Emotional Intelligence	
A. Objectivity	There is a huge advantage because I usually bring objectivity (I09, 101).
B. Serenity	Behave as if there was no time pressure and take the time to analyse and think and make a good decision and be calm (I09, 95).
C. Self-Awareness	C1. I know my mission. I happen to be a well-trained HR manager who can help companies and provide know-how (I05, 192).
	C2. Talk about things you know. Don't talk about things you don't know. Ask questions when you don't know. (I09, 89).
D. Empathy	That's empathy, strategic communication or more like advising, like consulting. But I think those are, those are important things (I13, 90).
5. Cognitive Skills	
A. Innovativeness and Creativity	There is no template for the way out of a crisis. You have to create new solutions yourself (I03, 76).
B. Goal-Orientation	Be target oriented, be results oriented (I10, 74).
C. Analytical Skills	The core skills are actually analysis. How do I interpret data, even if it is more complex (I14, 80).
D. Speed of Reaction	D1. I'm working at a very fast pace, that most people can't do (I17, 40).
	D2. Make decisions quickly and firmly (I17, 58).

4.6 Discussion

Management research frequently highlights the role of HRM and temporary managers in facilitating organisational change processes (Smid et al. 2006; Bruns 2014). Our findings corroborate this perspective while expanding it by examining specific HR decision-making processes in greater depth. Whereas prior studies predominantly characterise temporary managers as change agents (Caldwell 2003; Wright 2008), our research demonstrates that temporary executives also function as knowledge carriers and facilitators across various roles, particularly during complex HR-related transformations. This multifaceted engagement of temporary managers suggests that a more nuanced understanding of the human capital they contribute is necessary. Rather than being limited to the role of initiators or implementers of change, they play an important role in motivating employees, shaping the strategic discourse and legitimising change through professional authority. Their temporary status can increase their credibility in some contexts and allow them to act with greater neutrality or flexibility in politically sensitive environments.

Through a qualitative analysis of seventeen temporary executives, we identified three distinct typologies – *The Decider*, *The Advisor*, and *The Realiser* – each embodying different strategic orientations, decision-making logics, and leadership behaviours. *The Decider* is characterised by strategic foresight, decisiveness, and a strong ethical compass, often taking on high-stakes transformation mandates where authoritative leadership is needed. *The Advisor*, by contrast, demonstrates a collaborative, coaching-oriented approach, leveraging emotional intelligence and influencing through informal authority. *The Realiser* focuses on operational implementation and pragmatic problem-solving, ensuring the execution of strategic intent at the process level.

These differentiated roles suggest that temporary managers are far from a homogenous group; instead, they perform plural leadership functions (Denis et al. 2012) and adapt their behaviour to meet the evolving demands of the organisation. Our findings, therefore, call for a reassessment of temporary management that goes beyond generic change agent models and instead recognises the typological variance in how temporary executives operate.

Moreover, the temporary nature of these roles affords certain advantages in politically sensitive or highly volatile environments. In line with recent research on *Role Detachment* and *Institutional Work* (Lawrence et al. 2009; Tempelaar and Rosenkranz 2019), we find that temporary executives can act with greater neutrality and flexibility, unburdened by internal power dynamics or long-term reputation risks. This detachment often enhances their ability to execute unpopular but necessary HR decisions, legitimise change processes, and reframe organisational narratives in ways incumbent leaders may find politically untenable.

4.6.1 Implications for Theory and Practice

Two areas for theoretical contributions emerge from our research. First, we contribute to the research call by Mooney et al. (2017) by demonstrating the range of human capital that temporary managers can bring to an organisation. We expand the discourse on managerial temporality (Bakker 2010) by illustrating how temporary leaders can exert long-term strategic influence. While much of the existing literature focuses on the risks of temporary leadership (Inkson et al. 2001; Ballinger and Marcel 2010) – such as lack of commitment or organisational embeddedness – we highlight how temporariness can, under certain conditions, foster clarity, speed, and impartiality in decision-making. We shed light on the different strategic approaches that temporary managers apply to restore an organisation's profitability, contributing to a broader understanding of the daily tasks, decision-making processes, and competency profiles that managers bring to organisations in crisis situations. Based on these insights, we distinguish three typologies of temporary managers – *The Decider, The Advisor,* and *The Realise*r. Each typology reflects a different focus on their approaches and key competencies.

Secondly, building on Mintzberg's (1973; 1975) framework for managerial roles, our work contributes to the literature in two ways. On the one hand, we apply the framework to the specific field of temporary management to examine how these managers' interpersonal, informational, and decision-making roles manifest themselves in unique ways during temporary assignments. On the other hand, we enriched Mintzberg's (1973; 1975) framework by expanding the perceived role profiles of temporary managers to include the associated human capital, namely their daily tasks, HR decision-making processes and competency profiles. This represents a transfer and categorisation of the interpersonal, informational, and decisional roles of temporary managers, expanding Mintzberg's managerial role framework through the integration of human capital dimensions.

Our research also offers a range of practical contributions. It provides added value from the company's perspective by identifying and presenting a typology of temporary managers (*The Decider*, *The Advisor*, *The Realise*r). This allows companies to evaluate better and match the profile of temporary executives that best fills their needs, along with their tasks, roles, key competencies, and decision-making processes. For instance, a company undergoing rapid corporate resurgence might benefit most from *The Realiser* type, who excels at executing turnaround plans. In contrast, a company amid reorientation may require *The Advisor* type to provide critical guidance. This contribution ensures a more targeted and effective use of temporary managers, optimising the company's performance.

From the perspective of temporary managers, our study also offers value by shedding light on their diverse skill profiles and potential competency gaps, thereby indicating how they can enhance their effectiveness. This way, training needs can become transparent, for example, by strengthening emotional intelligence. In addition, broadening their understanding of the specific requirements of their roles can help interim managers better position themselves in the market and meet client expectations.

4.6.2 Limitations and Future Research

It is essential to acknowledge several limitations of the current study, particularly those stemming from the research environment. Firstly, the classification of the different typologies is partly based on the subjective self-perception of the interviewed interim managers. While we made efforts to complement this categorisation with objective job descriptions, inherent biases persist. In particular, using qualitative data collection through expert interviews introduces a potential for distortion that cannot be eliminated but is mitigated by various measures in the data collection and analysis (Miles and Huberman 1994). A second limitation concerns the sample, which is European, with a particular focus on German temporary managers. This geographic concentration may limit the generalisability of the findings to other contexts.

Given these limitations, we encourage future research to further investigate temporary management in crisis environments. In particular, the investigation and examination of the advantages of the three typologies of temporary managers with regard to the different stages of crises and the causes of crises offer interesting starting points for further research. In addition, the investigation of cross-cultural differences and the influence of management styles of temporary managers offer interesting starting points. Additionally to these broader research directions, we underscore the need for further investigation into the role of temporary managers in organisational crises and the relationship between their involvement and the success of corporate turnarounds.

4.7 Conclusion

This study identifies three distinct typologies of temporary managers based on the human capital and the roles they exhibit within organisations. The diverse daily tasks, reported HR decision-making processes and perceived necessary competencies reveal varying approaches and thus typologies of temporary executives and associated management roles. The insights are pertinent not only to the temporary managers themselves but also to struggling organisations seeking temporary support. The study thus helps to select the right bundle of human capital for the respective situation from both – organisational and temporary manager perspectives.

4.8 List of References

Ahn, Byeong S.; Cho, Sung S.; Kim, Chang Y. (2000): The Integrated Methodology of Rough Set Theory and Artificial Network for Business Failure Prediction. In: Expert Systems with Applications 18 (2), pp. 65–74. DOI: 10.1016/S0957-4174(99)00053-6.

Altman, Edward I. (1968): Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy. In: Journal of Finance 23 (4), pp. 589–609. DOI: 10.2307/2978933.

Bae, Jihun; Joo, Jeong H. (2021): CEO Turnover, Leadership Vacuum, and Stock Market Reactions. In: Applied Economics 53 (48), pp. 6752–6769. DOI: 10.1080/00036846.2021.1927969.

Bae, Jihun; Joo, Jeong H.; Park, Chul W. (2022): Differential Performance Impacts of Outsider and Insider Interim CEO Successions. In: Asia-Pacific Journal of Accounting & Economics 29 (6), pp. 1439–1468. DOI: 10.1080/16081625.2020.1828106.

Bakker, René M. (2010): Taking Stock of Temporary Organizational Forms: A Systematic Review and Research Agenda. In: International Journal of Management Reviews 12 (4), pp. 466–486. DOI: 10.1111/j.1468-2370.2010.00281.x.

Balgobin, Rolf; Pandit, Naresh R. (2001): Stages in the Turnaround Process: The Case of IBM UK. In: European Management Journal 19 (3), pp. 301–316. DOI: 10.1016/S0263-2373(01)00027-5.

Ballinger, Gary A.; Marcel, Jeremy J. (2010): The Use of an Interim CEO during Succession Episodes and Firm Performance. In: Strategic Management Journal 31 (3), pp. 262–283. DOI: 10.1002/smj.808.

Barker, Vincent L.; Mone, Mark A. (1994): Retrenchment: Cause of Turnaround or Consequence of Decline. In: Strategic Management Journal 15 (5), pp. 395–405. DOI: 10.1002/smj.4250150506.

Boyne, George A.; Meier, Kenneth J. (2009): Environmental Change, Human Resources and Organizational Turnaround. In: Journal of Management Studies 46 (5), pp. 835–863. DOI: 10.1111/j.1467-6486.2008.00813.x.

Bronnenmayer, Matias; Wirtz, Bernd W.; Göttel, Vincent (2016): Success Factors of Management Consulting. In: Review of Managerial Science 10 (1), pp. 1–34. DOI: 10.1007/s11846-014-0137-5.

Brown, Andrew D.; Stacey, Patrick; Nandhakumar, Joe (2008): Making Sense of Sensemaking Narratives. In: Human Relations 61 (8), pp. 1035–1062. DOI: 10.1177/0018726708094858.

Browning, Blair W.; McNamee, Lacy G. (2012): Considering the Temporary Leader in Temporary Work Arrangements: Sensemaking Processes of Internal Interim Leaders. In: Human Relations 65 (6), pp. 729–752. DOI: 10.1177/0018726711433615.

Bruns, Jürgen (2014): HR Development in Local Government: How and Why Does HR Strategy Matter in Organizational Change and Development? In: Business Research 7, pp. 1–49. DOI: 10.1007/s40685-014-0002-z.

Bruns, Jürgen; Kabst, Rüdiger (2005): Interim-Management: A Paradox for Leadership Research? In: Management Revue 16 (4), pp. 512–524. DOI: 10.5771/0935-9915-2005-4-512.

Brunsson, Nils (1982): The Irrationality of Action and Action Rationality: Decisions, Ideologies and Organizational Actions. In: Journal of Management Studies 19 (1), pp. 29–44. DOI: 10.1111/j.1467-6486.1982.tb00058.x.

Bruton, Garry D.; Ahlstrom, David; Li, Han-Lin (2010): Institutional Theory and Entrepreneurship: Where are We Now and Where Do We Need to Move in the Future? In: Entrepreneurship Theory and Practice 34 (3), pp. 421–440. DOI: 10.1111/j.1540-6520.2010.00390.x.

Bundy, Jonathan; Pfarrer, Michael D.; Short, Cole E.; Coombs, W. Timothy (2017): Crises and Crisis Management: Integration, Interpretation, and Research Development. In: Journal of Management 43 (6), pp. 1661–1692. DOI: 10.1177/0149206316680030.

Caldwell, Raymond (2003): Models of Change Agency: A Fourfold Classification. In: British Journal of Management 14 (2), pp. 131–142. DOI: 10.1111/1467-8551.00270.

Carmeli, Abraham; Sheaffer, Zachary (2009): How Leadership Characteristics Affect Organizational Decline and Downsizing. In: Journal of Business Ethics 86 (3), pp. 363–378. DOI: 10.1007/s10551-008-9852-7.

Child, John (1997): Strategic Choice in the Analysis of Action, Structure, Organizations and Environment: Retrospect and Prospect. In: Organization Studies 18 (1), pp. 43–76. DOI: 10.1177/017084069701800104.

Dandalt, Ed (2021): The Cyber-Work Performance of Managers in Education. In: Journal of Management Development 40 (3), pp. 151–167. DOI: 10.1108/JMD-01-2020-0011.

Denis, Jean-Louis; Langley, Ann; Sergi, Viviane (2012): Leadership in the Plural. In: Academy of Management Annals 6 (1), pp. 211–283. DOI: 10.5465/19416520.2012.667612.

Ditillo, Angelo (2004): Dealing With Uncertainty in Knowledge-Intensive Firms: The Role of Management Control Systems as Knowledge Integration Mechanisms. In: Accounting, Organizations and Society 29 (3–4), pp. 401–421. DOI: 10.1016/j.aos.2003.12.001.

Dubrovski, Drago (2009): Management Mistakes as Causes of Corporate Crises: Managerial Implications for Countries in Transition. In: Total Quality Management & Business Excellence 20 (1), pp. 39–59. DOI: 10.1080/14783360802614281.

Edvardsson, Ingi Runar; Durst, Susanne (2021): Human Resource Management in Crisis Situations: A Systematic Literature Review. In: Sustainability 13 (22), p. 12406. DOI: 10.3390/su132212406.

Eva, Nathan; Robin, Mulyadi; Sendjaya, Sen; van Dierendonck, Dirk; Liden, Robert C. (2019): Servant Leadership: A Systematic Review and Call for Future Research. In: The Leadership Quarterly 30 (1), pp. 111–132. DOI: 10.1016/j.leaqua.2018.07.004.

Farquhar, Katherine W. (1995): Not Just Understudies: The Dynamics of Short-Term Leadership. In: Human Resource Management (34) 1, pp. 51–70. DOI: 10.1002/hrm.3930340105.

Fisher, Jo-Anne; Newman, Alexander; Sendjaya, Sen (2024): Interim Leadership: A Systematic Literature Review and Future Research Agenda. In: Journal of Vocational Behavior 150 (8), p. 103974. DOI: 10.1016/j.jvb.2024.103974.

Flanagan, John C. (1954): The Critical Incident Technique. In: Psychological Bulletin 51 (4), pp. 327–358. DOI: 10.1037/h0061470.

Flatøy, Christer A. (2024): The Liability of Outsiderness: Professional Interim Managers and Their On-The-Job Challenges. In: Journal of Organizational Effectiveness: People and Performance 12 (5), pp. 24–40. DOI: 10.1108/JOEPP-10-2023-0456.

Förster, Charlotte; Paparella, Caroline; Duchek, Stephanie; Güttel, Wolfgang H. (2022): Leading in the Paradoxical World of Crises: How Leaders Navigate through Crises. In: Schmalenbach Journal of Business Research 74, pp. 631–657. DOI: 10.1007/s41471-022-00147-7.

Gioia, Dennis A.; Chittipeddi, Kumar (1991): Sensemaking and Sensegiving in Strategic Change Initiation. In: Academy of Management Review 16 (3), pp. 433–438. Available online at: https://www.jstor.org/stable/2486479 (retrieved on July 7, 2025).

Gioia, Dennis A.; Corley, Kevin G.; Hamilton, Aimee L. (2013): Seeking Qualitative Rigor in Inductive Research. In: Organizational Research Methods 16 (1), pp. 15–31. DOI: 10.1177/1094428112452151.

Glaser, Barney G.; Strauss, Anselm L. (2009): The Discovery of Grounded Theory. New Brunswick: Transaction Publishers.

Goleman, Daniel (1998): Working with Emotional Intelligence. New York, New York: Bantam.

Gordon, Myron J. (1971): Towards a Theory of Financial Distress. In: Journal of Finance 26 (2), pp. 347–356. DOI: 10.1111/j.1540-6261.1971.tb00902.x.

Goss, David; Bridson, Joanna (1998): Understanding Interim Management. In: Human Resource Management Journal 8 (4), pp. 37–50. DOI: 10.1111/j.1748-8583.1998.tb00179.x.

Gotteiner, Sharon; Mas-Machuca, Marta; Marimon, Frederic (2019): Fighting Organizational Decline: A Risk-Based Approach to Organizational Anti-Aging. In: Management Research Review 42 (11), pp. 1259–1277. DOI: 10.1108/MRR-09-2018-0367.

Grinyer, Peter H.; Mayes, David; McKiernan, Peter (1990): The Sharpbenders: Achieving a Sustained Improvement in Performance. In: Long Range Planning 23 (1), pp. 116–125. DOI: 10.1016/0024-6301(90)90013-T.

Hambrick, Donald C.; Schecter, Stephen M. (1983): Turnaround Strategies for Mature Industrial-Product Business Units. In: Academy of Management Journal 26 (2), pp. 231–248. Available online at: https://www.jstor.org/stable/255972 (retrieved on July 7, 2025).

Hofer, Charles W. (1980): Turnaround Strategies. In: Journal of Business Strategy 1 (1), pp. 19–31. DOI: 10.1108/eb038886.

Holcomb, Tim R.; Holmes Jr., R. Michael; Connelly, Brian L. (2009): Making the Most of What You Have: Managerial Ability as a Source of Resource Value Creation. In: Strategic Management Journal 30 (5), pp. 457–485. DOI: 10.1002/smj.747.

Huy, Quy N. (2001): In Praise of Middle Managers. In: Harvard Business Review 79 (8), pp. 72–79. Available online at: https://hbr.org/2001/09/in-praise-of-middle-managers (retrieved on July 7, 2025).

Inkson, Kerr; Heising, Angela; Rousseau, Denise M. (2001): The Interim Manager: Prototype of the 21st-Century Worker? In: Human Relations 54 (3), pp. 259–284. DOI: 10.1177/0018726701543001.

Intintoli, Vincent J.; Zhang, Andrew; Davidson, Wallace N. (2014): The Impact of CEO Turnover on Firm Performance around Interim Successions. In: Journal of Management & Governance 18 (2), pp. 541–587. DOI: 10.1007/s10997-012-9253-2.

Jas, Pauline (2013): The Role of Interim Managers in Performance Improvement: Evidence from English Local Authorities. In: Public Money & Management 33 (1), pp. 15–22. DOI: 10.1080/09540962.2013.744890.

Jibril, Halima; Wishart, Maria; Roper, Stephen (2023): From Adversity to Advice: Survival Threats as a Trigger for Sustained Engagement with External Business Support in Small Firms. In: International Small Business Journal: Researching Entrepreneurship 41 (5), pp. 488–507. DOI: 10.1177/026624262211050.

Kim, Youngshin; Bae, Johngseok; Yu, Gyu-Chang (2013): Patterns and Determinants of Human Resource Management Change in Korean Venture Firms after the Financial Crisis. In: The International Journal of Human Resource Management 24 (5), pp. 1006–1028. DOI: 10.1080/09585192.2012.743473.

Kranz, Olaf; Steger, Thomas (2013): The Impact of the Global Financial Crisis on Employee Participation – Two German Case Studies. In: International Journal of Manpower 34 (3), pp. 252–270. DOI: 10.1108/IJM-04-2013-0081.

Kurke, Lance B.; Aldrich, Howard E. (1983): Note – Mintzberg Was Right!: A Replication and Extension of the Nature of Managerial Work. In: Management Science 29 (8), pp. 975–984. DOI: 10.1287/mnsc.29.8.975.

Labaronne, Leticia; Müller, Andrea (2024): Mapping Out the Roles of Top Management in Nonprofit Arts and Cultural Organizations. In: The Journal of Arts Management, Law, and Society 54 (1), pp. 1–16. DOI: 10.1080/10632921.2023.2285476.

Lawrence, Thomas B.; Suddaby, Roy; Leca, Bernard (2009): Introduction: Theorizing and Studying Institutional Work. In: Lawrence, Thomas B.; Suddaby, Roy; Leca, Bernard (Eds.): Institutional Work: Actors and Agency in Institutional Studies of Organizations. Cambridge: Cambridge University Press, pp. 1–28.

Lewis, Marianne W.; Smith, Wendy K. (2022): Reflections on the 2021 Decade Award: Navigating Paradox Is Paradoxical. In: Academy of Management Review 47 (4). DOI: 10.5465/amr.2022.0251.

Lincoln, Yvonna S.; Guba, Egon G. (1985): Naturalistic Inquiry. Thousand Oaks, California: Sage.

Liou, Dah-Kwei; Smith, Malcolm (2007): Financial Distress and Corporate Turnaround: A Review of the Literature and Agenda for Research. In: Journal of Accounting, Auditing and Accountability 13 (1), pp. 76–116. DOI: 10.2139/ssrn.925596.

Malik, Ashish; Sanders, Karin (2021): Managing Human Resources during a Global Crisis: A Multilevel Perspective. In: British Journal of Management 32 (4), pp. 1–19. DOI: 10.1111/1467-8551.12484.

Martinko, Mark J.; Gardner, William L. (1985): Beyond Structured Observation: Methodological Issues and New Directions. In: The Academy of Management Review 10 (4), p. 676. DOI: 10.2307/258038.

Milburn, Thomas W.; Schuler, Randall S.; Watman, Kenneth H. (1983): Organizational Crisis. Part I: Definition and Conceptualization. In: Human Relations 36 (12), pp. 1141–1160. DOI: 10.1177/001872678303601205.

Miles, Matthew B.; Huberman, A. Michael (1994): Qualitative Data Analysis. An Expanded Sourcebook. 2. Edition. Thousand Oaks, California: Sage.

Miller, Danny; Friesen, Peter H. (1984): A Longitudinal Study of the Corporate Life Cycle. In: Management Science 30 (10), pp. 1161–1183. DOI: 10.1287/mnsc.30.10.1161.

Mintzberg, Henry (1973): The Nature of Managerial Work. New York, New York: Harper & Row.

Mintzberg, Henry (1975): The Manager's Job: Folklore and Fact. In: Harvard Business Review 53 (4), pp. 49–62. Available online at: https://hbr.org/1990/03/the-managers-job-folklore-and-fact (retrieved on July 7, 2025).

Mooney, Christine H.; Semadeni, Matthew; Kesner, Idalene F. (2017): The Selection of an Interim CEO: Boundary Conditions and the Pursuit of Temporary Leadership. In: Journal of Management 43 (2), pp. 455–475. DOI: 10.1177/0149206314535433.

Mulder, Mauk; van Eck, Jan. R. Ritsema; de Jong, Rendel D. (1971): An Organization in Crisis and Non-Crisis Situations. In: Human Relations 24 (1), pp. 19–41. DOI: 10.1177/001872677102400102.

O'Neill, Hugh M. (1986): Turnaround and Recovery: What Strategy Do You Need? In: Long Range Planning 19 (1), pp. 80–88. DOI: 10.1016/0024-6301(86)90131-7.

O'Shaughnessy, Nicholas J. (1986): Tactics for Turnaround. In: Management Decision 24 (3), pp. 3–6. DOI: 10.1108/eb001404.

Patton, Michael Q. (2015): Qualitative Research & Evaluation Methods: Integrating Theory and Practice. 4. Edition. Los Angeles, California: Sage.

Pearson, Christine M.; Mitroff, Ian I. (1993): From Crisis Prone to Crisis Prepared: A Framework for Crisis Management. In: Academy of Management Perspectives 7 (1), pp. 48–59. DOI: 10.5465/ame.1993.9409142058.

Pinkwart, Andreas; Schingen, Gideon; Pannes, Anna T.; Schlotböller, Dirk (2022): Improving Resilience in Times of Multiple Crisis. In: Schmalenbach Journal of Business Research 74, pp. 763–786. DOI: 10.1007/s41471-022-00150-y.

Pretorius, Marius (2008): When Porter's Generic Strategies Are Not Enough: Complementary Strategies for Turnaround Situations. In: Journal of Business Strategy 29 (6), pp. 19–28. DOI: 10.1108/02756660810917200.

Rohrbeck, René; Kum, Menes E. (2018): Corporate Foresight and Its Impact on Firm Performance: A Longitudinal Analysis. In: Technological Forecasting and Social Change 129, pp. 105–116. DOI: 10.1016/j.techfore.2017.12.013.

Rosenthal, Uriel; Hart, Paul (1991): Experts and Decision Makers in Crisis Situations. In: Knowledge 12 (4), pp. 350–372. DOI: 10.1177/107554709101200402.

Ruppel, Christopher; Stranzl, Julia; Einwiller, Sabine (2022): Employee-Centric Perspective on Organizational Crisis: How Organizational Transparency and Support Help to Mitigate Employees' Uncertainty, Negative Emotions and Job Disengagement. In: Corporate Communications: An International Journal 27 (5), pp. 1–22. DOI: 10.1108/CCIJ-04-2022-0045.

Schein, Edgar H. (1999): Process Consultation Revisited: Building the Helping Relationship. Reading, Massachusetts: Addison-Wesley.

Schendel, Dan; Patton, George R.; Riggs, James (1976): Corporate Turnaround Strategies: A Study of Profit Decline and Recovery. In: Journal of General Management 3 (3), pp. 3–11. DOI: 10.1177/030630707600300301.

Scherrer, Philipp S. (2003): Management Turnarounds: Diagnosing Business Ailments. In: Corporate Governance 3 (4), pp. 52–62. DOI: 10.1108/14720700310497122.

Schoenberg, Richard; Collier, Nardine; Bowman, Cliff (2013): Strategies for Business Turnaround and Recovery: A Review and Synthesis. In: European Business Review 25 (3), pp. 243–262. DOI: 10.1108/09555341311314799.

Schön, Donald A. (1983): The Reflective Practitioner: How Professionals Think in Action. New York, New York: Basic Books.

Selby, John (2021): The International Network of Interim Manager Associations (INIMA) – The 2021 European Survey INIMA. Available online at: https://www.inima.management/survey-1 (retrieved on July 7, 2025).

Selby, John (2024): The International Network of Interim Manager Associations (INIMA) – The 2024 European Survey INIMA. Available online at: https://www.inima.management/2024 (retrieved on July 7, 2025).

Shapira, Zur; Dunbar, Roger L. (1980): Testing Mintzberg's Managerial Roles Classification Using an In-Basket Simulation. In: The Journal of Applied Psychology 65 (1), pp. 87–95. DOI: 10.1037/0021-9010.65.1.87.

Simon, Herbert A. (1955): A Behavioral Model of Rational Choice. In: The Quarterly Journal of Economics 69 (1), pp. 99–118. DOI: 10.2307/1884852.

Smid, Gerhard; van Hout, Eelco; Burger, Yvonne (2006): Leadership in Organisational Change: Rules for Successful Hiring in Interim Management. In: Journal of Change Management 6 (1), pp. 35–51. DOI: 10.1080/14697010600578601.

Smith, Malcolm; Graves, Christopher (2005): Corporate Turnaround and Financial Distress. In: Managerial Auditing Journal 20 (3), pp. 304–320. DOI: 10.1108/02686900510585627.

Snyder, Neil H.; Wheelen, Thomas L. (1981): Managerial Roles: Mintzberg and the Management Process Theorists. In: Academy of Management Proceedings, pp. 249–253. DOI: 10.5465/ambpp.1981.4976861.

Sturdy, Andrew (2011): Consultancy's Consequences? A Critical Assessment of Management Consultancy's Impact on Management. In: British Journal of Management 22 (3), pp. 517–530. DOI: 10.1111/j.1467-8551.2011.00750.x.

Tempelaar, Michiel P.; Rosenkranz, Nicole A. (2019): Switching hats: The Effects of Role Transition on Individual Ambidexterity. In: Journal of Management 45 (4), pp. 1517–1541. DOI: 10.1177/0149206317714312.

Tengblad, Stefan (2006): Is There a 'New Managerial Work'? A Comparison with Henry Mintzberg's Classic Study 30 Years Later. In: Journal of Management Studies 43 (7), pp. 1437–1461. DOI: 10.1111/j.1467-6486.2006.00651.x.

Trahms, Cheryl A.; Ndofor, Hermann A.; Sirmon, David G. (2013): Organizational Decline and Turnaround: A Review and Agenda for Future Research. In: Journal of Management 39 (5), pp. 1277–1307. DOI: 10.1177/0149206312471390.

Trunk, Anna; Birkel, Hendrik (2022): No Resilience Without Partners: A Case Study on German Small and Medium-Sized Enterprises in the Context of COVID-19. In: Schmalenbach Journal of Business Research 74, pp. 537–574. DOI: 10.1007/s41471-022-00149-5.

Van Maanen, John (1979): The Fact of Fiction in Organizational Ethnography. In: Administrative Science Quarterly 24 (4), pp. 539–550. DOI: 10.2307/2392360.

Whitney, John O. (1987): Turnaround Management Every Day. In: Harvard Business Review 65 (5), pp. 49–55. Available online at: https://hbr.org/1987/09/turnaround-management-every-day (retrieved on July 7, 2025).

Wickert, Christopher; de Bakker, Frank G. A. (2018): Pitching for Social Change: Toward a Relational Approach to Selling and Buying Social Issues. In: Academy of Management Discoveries 4 (1), pp. 50–73. DOI: 10.5465/amd.2015.0009.

Woods, Stephen A.; Diprose, Nick; Murphy-Diprose, Mary; Geoff, Thomas (2020): Effective Interim Leadership and Management: Development of a Cyclical Model of Interim Assignments. In: Journal of Organizational Effectiveness: People and Performance 7 (2), pp. 173–190. DOI: 10.1108/JOEPP-10-2019-0094.

Wright, Christopher (2008): Reinventing Human Resource Management: Business Partners, Internal Consultants and the Limits to Professionalization. In: Human Relations 61 (8), pp. 1063–1086. DOI: 10.1177/0018726708094860.

Zambrano Farias, Fernando; Valls Martínez, María del Carmen; Martín-Cervantes, Pedro Antonio (2021): Explanatory Factors of Business Failure: Literature Review and Global Trends. In: Sustainability 13 (18), p. 10154. DOI: 10.3390/su131810154.

5 Comprehensive Discussion

This chapter discusses the main findings of this dissertation and interlinks the results of the three studies that form the core of this thesis. To ensure a structured discussion, the findings are summarised and analysed through the lens of three vital perspectives of *technology*, *organisation*, and *human* to better understand the adoption of data-driven decision-making in HRM. These perspectives were chosen as they proved to be central to the adoption of HR-related information technology for decision-making in organisations over the course of the investigation. Furthermore, these three perspectives are reflected in current literature on Information System adoption (see e.g. Yusof et al. 2008; Srivastava et al. 2020; Xu and Lu 2022) and thus form the basis for data-driven decision-making.

It should be noted that this dissertation analyses the organisational perspective from a broad viewpoint, explicitly incorporating environmental factors that influence organisational behaviour. It is argued that these factors are closely linked to internal dynamics and shape both strategic and operational decisions; they are therefore considered an integral part of the organisational context. In related literature, which is often grounded in the TOE framework (e.g. Pumplun et al. 2019; Chatterjee et al. 2021; Gurusinghe et al. 2021; Neumann et al. 2022; Coolen et al. 2023), environmental factors are occasionally treated as a separate dimension alongside technological and organisational factors.

Figure 14 visually illustrates which perspective of the overarching research objective is covered by which study. Study one primarily sheds light on the technological perspective, whereas studies two and three focus on the organisational and human dimensions respectively. These results underscore the multifaceted nature of adopting data-driven HR decision-making, emphasising the need for a holistic approach.

Each of the three perspectives is covered in a separate section (sections 5.1 to 5.3). Additionally, section 5.4 is dedicated to a discussion of the relationship between the technological and human perspectives as these perspectives reveal deep interconnections in the second study and in current literature (see also Xu and Lu 2022). Finally, this dissertation concludes with a set of practical recommendations (section 5.5) for organisations seeking to adopt data-driven HR decision-making. These practical measures are derived from the results of the three studies, further considerations, and the current literature. They serve as a roadmap for organisations to successfully overcome technological, organisational, and human challenges. Section 5.6 closes the dissertation with the conclusion.

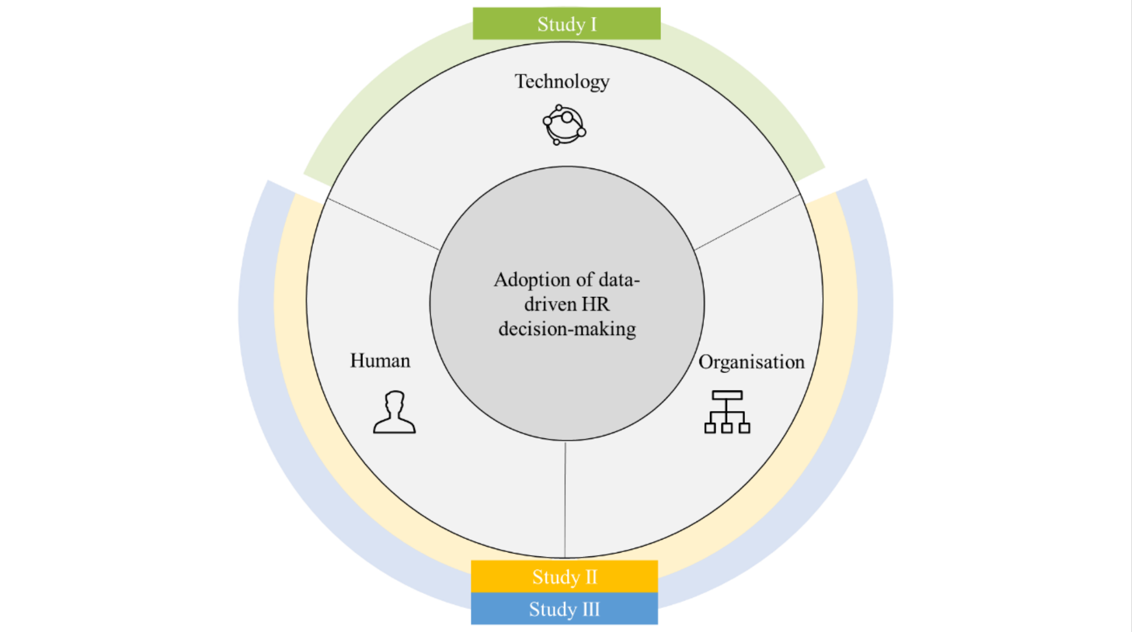

Figure 14: Contribution of the three studies to the overarching research objective

5.1 Technological Perspective

Study one primarily sheds light on the technological aspects of adopting data-driven HR decision-making. Firstly, it empirically demonstrates that **selecting suitable analysis methods** is an important prerequisite for the process. When considering suitable alternatives, it is particularly important to pay attention to the characteristics as well as the associated advantages and disadvantages of the methods. Various algorithms and ML models for predicting voluntary employee turnover were evaluated in the first study, focusing particularly on the two key characteristics of predictive performance and transparency. Testing different models is a typical ML practice to find the most suitable model for the existing databases (Raschka 2018; Chowdhury et al. 2023b).

The selection and evaluation of suitable analysis methods is of critical importance when introducing data-driven HR decision-making. When selecting methods, their properties should be critically scrutinised so that they can be used purposefully for data-driven decisions. In the HR context in particular, transparency and traceability should be crucial components in the selection of suitable methodologies and algorithms to understand the rationale behind them (Chowdhury et al. 2023b). This lays the foundation for uncovering biases that can arise through AI, as seen in the example of Amazon where a recruitment tool systematically discriminates against women (Dastin 2022). Speer (2021) also highlights the potential discriminatory outcomes that can arise from ML algorithms. This underlines the urgent need to critically scrutinise the characteristics of the analysis methods in detail and to be aware of their weaknesses. That scrutinisation allows for weakness counteraction strategies to be developed and executed, which allows the analysis methods to be used in a targeted manner.

Secondly, study one provides evidence that the prediction of voluntary employee turnover with existing data is possible to a certain extent, and the **prediction performance varies between different algorithms and ML models**. In that specific use case, the ML model *Random Forest* offers the highest predictive performance compared to linear regressions and other ML models, making it the most suitable algorithm.

These findings underscore the need to utilise advanced predictive analytics to capture complex interactions, thereby enhancing HR decision-making in areas such as employee retention, workforce planning, and talent management. Many different data points should be included in the database for the algorithm because HR decisions like (voluntary) employee turnover are generally complex processes with many reasons and causes that may or may not lead to leaving a job (e.g. Holtom et al. 2008; Hom et al. 2017; Rombaut and Guerry 2018). The latest developments in ML hold enormous potential to support HR decision-making as they can incorporate many predictors and better capture their complex interactions. The results of the first study included in this thesis provide empirical evidence that more sophisticated algorithms with higher predictive performance are more likely to capture complex interactions and thus reliably predict voluntary employee turnover. Related studies, like the ones by Choudhury et al. (2021) and Chowdhury et al. (2023b), rely on artificially simulated datasets rather than real-world data. Their findings differ from the conclusions presented in the first study of this thesis, which may be due to the limitations inherent in simulated environments that potentially not capture the full complexity or variability of real-world conditions. This contrast highlights the added value of using real-world data, particularly when integrated with advanced ML models in HR contexts. By systematically integrating sophisticated ML models into HR processes and extensively incorporating various data points, organisations have the potential to make more evidence-based decisions that go beyond intuition and traditional analytical methods (McCartney and Fu 2022a).

Third, and related to points one and two, the first study provides evidence that the **high predictive performance** of the *Random Forest* ML model **is offset by its low transparency**. In other words, the specific model offers a powerful way to predict voluntary employee turnover; however, it has limitations in terms of transparency and is therefore not easily comprehensible (see also Arrieta et al. 2020; Oswald et al. 2020). Hence, study one argues that these models and explanations should only be used when the predictive performance of the non-transparent ML models is higher, as otherwise their use is not justified.

From a practical HR perspective, this finding highlights the importance of striking a balance between predictive performance and transparency. Transparency is a challenge, especially in HR contexts, as managers often struggle to understand how AI algorithms generate results based on proprietary systems or complex mathematical models (Shin and Park 2019). ML operators, HR managers, and other responsible parties should be aware of this trade-off between predictive performance and transparency, critically examine the models and algorithms used, and actively choose the alternatives to ensure justified use.

Fourth, the first study of this thesis emphasises the need to apply **post-hoc explanatory methods** to provide a certain degree of transparency when using complex, non-transparent models. The use of local and global post-hoc explanatory methods offers an overview of the predictors leading to the ML prediction, while the ML literature offers a wide range of different methods (e.g. see Molnar 2022; Lyu and Wu 2025). The two global methods employed in study one are *Global Feature Importance* and *Accumulated Local Effects* (ALE). Simplified, *Global Feature Importance* indicates the significance of a predictor for the prediction in general (Molnar 2022). ALE generalises how a single predictor influences the predictions on average as well as indicates the strength and positive or negative contribution to the prediction (Apley and Zhu 2020). Local post-hoc explanatory methods in study one, namely *SHapley Additive exPlanations* (SHAP), give each predictor a value based on how much it helps the model make its prediction (Lyu and Wu 2025). Thus, this method provides a detailed explanation of how a particular prediction is achieved, highlighting its various predictors and their corresponding strengths.

The limited transparency and interpretability of algorithms emerge as a major obstacle to realising the expected benefits, particularly when aiming to translate data-driven decisions into strategies (Makarius et al. 2020; Chowdhury et al. 2022; Lyu and Wu 2025). Therefore, the use of explanatory methods for complex algorithms is crucial to gain insight into the ML process and undertakings, especially in HRM. HR decisions have a direct impact on organisational performance, HR strategy and – most importantly – individual lives (Chowdhury et al. 2023b). The various explanatory methods provide insights into the effects and strengths of the predictors and thus give an understanding of the way the algorithms operate. This ability to interpret and validate the algorithmic results is also essential to reducing bias, ensuring fairness, and fostering trust in data-driven HR practices (Satell and Sutton 2019; Lyu and Wu 2025). Without transparency, the risk of misinterpretation or ethical concerns such as biased decision-making could hinder the adoption of data-driven practices in HRM. Therefore, a clear explanatory framework is necessary, otherwise HR professionals or managers will be reluctant to adopt data-driven decision-making processes due to reputational or legal risks (Rai 2020; Edwards et al. 2022; Chowdhury et al. 2023a; Chowdhury et al. 2023b).

Finally, from a technological perspective, the first study of this thesis recommends a **combination of** inductive ML methods and the deductive use of traditional **approaches** to optimise HR decision-making. Evidence from sophisticated analysis should be challenged and verified carefully with information and data from other sources to ensure the validity of the results as well as to avoid biases.

The need for a hybrid approach to data-driven HR decisions is clear. While ML models can provide powerful insights into the data, it is important to cross-validate these results with other data, traditional HR expertise, and business knowledge (see also Aguinis et al. 2024) to prevent misinterpretation. This ensures that HR decisions remain both data-based and contextually grounded, thus contributing to a straighter adoption of data-driven HR decision-making in organisations.

5.2 Organisational Perspective

By examining two fundamentally different organisational environments, this dissertation offers a comprehensive perspective that improves the understanding of how organisational factors might influence the adoption of data-driven HR decision-making. By comparing a German federal agency (first and second studies) with the context of temporary management in crisis situations across various organisations (third study), clear structural, cultural and procedural dynamics become apparent.

Studies one and two of this thesis use an in-depth case investigation to examine the specific challenges faced by a public sector organisation in the process of adopting innovative data-driven HR decision-making. In general, federal agencies (in Germany) are characterised by the absence of market competition and strict legal and bureaucratic frameworks as well as a strong emphasis on transparency, accountability, and procedural compliance (Richter 2012; Fredriksson and Pallas 2016; Margetts and Dorobantu 2019; Desouza et al. 2020; Mikalef et al. 2022). The adoption of advanced technologies for HR decision-making – predictive analytics in this specific case – is constrained by strict regulatory frameworks regarding data protection standards and a multi-level stakeholder approval process. The processes to adopt advanced technology like this are time-consuming as they require a detailed assessment of the potential impacts on the workforce and alignment with legal mandates. Additionally, the investigated federal agency demonstrates a resistance to change – especially concerning technological innovation – that is deeply rooted in its organisational culture (see study two). This cultural resistance seems to be a major organisational obstacle to the introduction of data-driven approaches. Despite the aforementioned conditions, the examined federal agency is determined to actively address the pain points of voluntary employee turnover. To this end, innovative approaches are to be developed with the aim of better understanding the causes and establishing sustainable measures against voluntary turnover. The federal agency is providing substantial financial resources to support this process.

In contrast, the third study in this thesis examines several cases involving temporary managers operating in organisations with high-pressure and time-sensitive environments. These managers are hired with the objective to lead organisations through crises, restructurings, or strategic transition by taking carefully considered HR decisions. Here, the organisational priority shifts to enabling quick and well-founded decisions to efficiently guide the organisation out of crises through decisions with far-reaching consequences. These dynamic environments require effective implementations of initiatives and rapid decision-making approaches. The crisis-driven organisations prioritise speed and impact. Decision-making in these contexts seems to be more pragmatic, time-sensitive, and frequently based on incomplete information. Temporary managers often work within flatter organisational structures and enjoy greater autonomy, allowing them to sidestep lengthy procedures and act decisively. However, while time constraints enable quick analyses at a lower level, the use of more advanced methods such as predictive analytics is limited. The temporary managers in the study tend to use data analysis at the stage of descriptive analytics such as reports, dashboards or Key Performance Indicators (KPIs) if anything at all. They state that they usually have no opportunity to use more advanced methodological approaches due to a lack of available technology and data that is of sufficient quality. Temporary managers often report mixed feelings among employees and management regarding their willingness to change the organisation. Some are willing to adapt, while others refuse to accept that the organisation will not be able to overcome the crisis without changing.

These two research environments with different organisational circumstances illustrate that the adoption of data-driven HR decision-making is deeply embedded in the organisational context. Among other things, the decision-making logic and structural conditions, organisational culture and openness to change, financial resources, and motivation for the adoption can influence whether and how tools for data-driven HR decision-making are adopted.

First, the **structural conditions and decision-making logic** in the two research environments appear to have a significant impact on the adoption of data-driven HR decision-making. Decision-making is typically formalised, legally bound, and focused on compliance, transparency, and procedural consistency in public sector organisations (e.g. Richter 2012; Fredriksson and Pallas 2016; Margetts and Dorobantu 2019; Mikalef et al. 2022). These characteristics create a landscape that potentially hinders innovation and creates structural and cultural barriers to the swift adoption of new, data-driven approaches (see e.g. Levenson 2018). In the context of AI, Margetts and Dorobantu (2019) point out that there are significant challenges to adoption, particularly in the public sector. They highlight that these challenges stem from a lack of technical in-house expertise, risks related to the misuse of AI such as security risks and privacy concerns, the need to ensure transparency in AI tools, moral dilemmas regarding appropriate contexts for the use of AI, and ethical concerns such as ensuring non-discrimination (Margetts and Dorobantu 2019). Moreover, decision-making processes are often multi-layered, involving numerous stakeholders and approval loops. That further impedes responsiveness and agility. In contrast, crisis-driven organisations, particularly those led by temporary managers, prioritise speed and impact. Decision-making in these contexts is pragmatic, time-sensitive, and frequently based on incomplete information. Temporary managers often work within flatter organisational structures and enjoy greater autonomy, allowing them to bypass lengthy procedures and quickly utilise descriptive analytics such as KPIs or benchmarks. Overall, these differences in decision-making logic and structural flexibility seem to have an impact on the adoption of data-driven HR decision-making, resulting in varying progress.

Secondly, and interwoven with the first point, the **organisational culture and openness to change** seem to play an important role in the adoption process of data-driven HR decision-making. Study two reveals that the federal agency is reluctant to adopt data-driven HR decision-making processes due in part to strict data protection laws, but also in part to its organisational culture. It tends to have a deeply rooted stability-oriented culture, reflecting a resistance to change (especially changes involving technological innovations). While there is often a greater openness to change due to urgency in the crisis context, the temporary managers in study three report that the willingness to embrace transformation varies among employees and can be accompanied by emotional resistance or uncertainty. Ultimately, while crises may create a window of opportunity for change, entrenched organisational cultures and emotional barriers can still significantly hinder the adoption of technological innovations. In summary, organisational culture appears to be a critical factor in the adoption of data-driven HR practices, especially in terms of how open the organisation is to change. Similar conclusions are drawn in the current literature, as Nam et al. (2019) note that a lack of data-driven culture is a barrier to the adoption of business analytics. Van den Heuvel and Bondarouk (2017) also argue that a data-driven culture is crucial for adopting data-driven HR decision-making.

Thirdly, the two research environments reflect different **baseline conditions in terms of financial resources,** which are mirrored, for example, in access to technology and the availability of data and expertise in the field of data analytics. The federal agency generally has access to technical infrastructure due to provided budgets. In addition, the public sector organisation disposed of a dedicated data analytics team with advanced skills, and it draws on external expertise from a consultancy. Conversely, organisations in crisis often lack the financial resources to invest in new technologies and the necessary infrastructure, which often leads to a shortage of high-quality data, advanced analytics technology, and analytics skills. Instead, they rely on basic tools such as reports and dashboards. These baseline conditions in terms of financial resources influence which technologies the organisations can adopt for data-driven HR decision-making. Several authors, like Min (2021), Gurusinghe et al. (2021), as well as Mikalef and Krogstie (2020), draw similar conclusions regarding the need for financial resources, while Coolen et al. (2023) highlight financial support as a heritage mechanism.

Fourth, the **motivation for the adoption** of data-driven HR decision-making differs across the two research environments. In this context, Desouza et al. (2020) highlight that the goal of initiatives is determined by the natures of the environment. The overarching goal of the federal agency using the predictive analytics tool is to increase efficiency by reducing voluntary employee turnover in conjunction with higher employee satisfaction, including through increased fairness. By contrast, the goal of crisis-driven organisations is short-term stabilisation and navigating transitions with speed and effectiveness taking precedence over procedural accuracy, as reported by the temporary managers. McCartney and Fu (2022b) highlight that, especially in disruptive times, such as crises like the Covid-19 pandemic, data-driven HR decision-making presents opportunities for navigating leadership and supporting transitions quickly. Ultimately, the motivation for adopting data-driven HR practices varies depending on the organisational environment that shapes organisational behaviour. Schaefer et al. (2021) support this conclusion. Their findings from the perspective of employees at a public sector organisation in Germany suggest that one challenge lies in the strategic alignment. The review by Margherita (2022) underscores this, identifying a wide range of concepts and sources related to the employee-related and organisational value of HR analytics, encompassing topics such as wage transparency and strategic change.

Overall, the studies included in this thesis demonstrate that organisational factors significantly shape the adoption of data-driven HR decision-making. Whether in highly regulated public sector organisations or rapidly changing crisis scenarios, the success of adopting data-driven approaches seems to be determined by an organisation's decision-making logic and structural conditions, culture and openness to change, baseline financial conditions, and motivation for introduction.

5.3 Human Perspective

Studies two and three contribute to a better understanding of the human perspective on adopting data-driven HR decision-making. As current research focuses almost exclusively on the adoption of data-driven decision-making from an organisational perspective, the second study of this thesis advances the rare understanding of the individual perspective. It explores the individual beliefs and experiences that lead to the adoption of data-driven HR decision-making (see also Vargas et al. 2018). The study further characterises potential users' underlying *Attitude*, *Perceived Behavioural Control* (PBC), and *Normative Drivers* regarding the intention to adopt data-driven HR decision-making based on the *Theory of Planned Behaviour* (TPB) (Ajzen 1991). The study employs a tool to facilitate discussion with the various employees on adoption, using a concrete and practical example, a ML-based tool for predicting voluntary employee turnover.

Relating to the attitude of individuals, the study identified the compatibility of tools and tasks, improving practices through innovation and personal concerns as crucial.

The results of study two suggest that the intention to adopt data-driven HR decision-making depends on its perceived **compatibility** with existing work processes and decisions. Differences in the assessment of technology adoption (*task-technology fit*) reveal that not all users perceive the added value and integration capabilities of a data-driven tool in the same way. Furthermore, in the specific example from study two, the majority of interviewees saw potential in identifying new factors influencing voluntary employee turnover. This suggests that data-driven HR decision-making is particularly well-received when it offers added value through *new insights*. Interestingly, the *consistency of predictions with personal intuition* significantly influences a potential user's attitude. This suggests that acceptance improves if results confirm their own assessment.

While some respondents positively assess the **innovative potential** of data-driven HR decision-making to improve existing HR processes such as workforce planning, others express concerns about *the implementation effort* and consequently the cost-benefit ratio. This illustrates that *technological innovation* alone is insufficient; and thus, perceived practicality is crucial.

Additionally, some interviewees fear the **potential misuse** of the tool. For example, excessive monitoring of employees or misinterpretation of data could lead to unfair treatment. Overall, ethical issues and protection against misuse seem to play a leading role in the intention to adopt data-driven HR decision-making.

Study two highlights that users' attitudes towards the intention to adopt data-driven HR decision-making tools are influenced by the extent to which they are compatible with existing tasks, the extent to which they provide new insights, and the extent to which they correspond with personal intuition. Shet et al. (2021) argue that the complexity of analytics in HR is a contributing factor influencing its adoption. It is therefore particularly important that results are rationally explainable and represent a meaningful addition rather than a contradiction to human intuition (Boudreau and Cascio 2017). Decision-makers in HR often rely on experience, domain knowledge, and intuition when making decisions (Highhouse 2008; Lodato et al. 2011; Miles and Sadler-Smith 2014). If data-driven recommendations starkly oppose these instincts without clear explanations, they may be met with scepticism or outright rejection. This can also lead to drawbacks, as the study by Alon-Barkat and Busuioc (2023) demonstrates, as people tend to follow algorithmic advice when it aligns with their existing stereotypes. Instead, data insights should serve as an augmentation of human decision-making, offering new perspectives and identifying patterns that might otherwise go unnoticed. In the study by Schaefer et al. (2021) about general AI adoption in the public sector, technical compatibility is also an important component. In their interviews, the compatibility of IT systems with the new AI technology is highlighted as being significant.

Additionally, the adoption of data-driven HR decision-making depends on whether users can clearly see improvement in the organisational landscape because of it. Simply implementing advanced analytics is not enough. Decision-makers must be able to recognise how data-driven insights improve efficiency, accuracy, and strategic outcomes. The results of Schaefer et al. (2021), Shet et al. (2021), and Bentvelzen et al. (2025) confirm this finding. Schaefer et al. (2021) report that the perceived direct benefits of AI technologies encourage their adoption in municipalities. Shet et al. (2021) conclude that the perceived usefulness of HR Analytics is crucial for its adoption, while Bentvelzen et al. (2025) emphasise that both performance expectancy and effort expectancy are conducive conditions that facilitate the use of HR Analytics technology. If the perceived value does not outweigh the effort required to integrate and use the tool, resistance is likely. Organisations should therefore focus on providing practical, actionable insights rather than overwhelming users with complex data outputs that lack relevance to their decision-making needs (Boudreau and Cascio 2017).

The concerns expressed by the study participants demonstrate that, beyond functionality and practical benefits, critical considerations play a decisive role in the adoption of data-driven HR decision-making tools. Fears around misuse like excessive employee surveillance or misinterpreting data in ways that lead to biased or unfair decisions reflect broader anxieties about data privacy, autonomy, and how algorithmic decision making affects individuals. These concerns can significantly hinder the intention to adopt advanced tools, especially if employees or HR managers perceive that data-driven tools are not being used constructively. It highlights the need for clear ethical guidelines, transparent governance, and accountability mechanisms to ensure the responsible adoption and use, especially in the HRM context (see e.g. Bannister and Connolly 2020; McCartney and Fu 2022b).

The results of study two indicate that the PBC for introducing data-driven HR decision-making is not solely dependent on technology-related aspects, but also on the perceptions and skills of the users. Three key drivers significantly influence the PBC regarding the intention to adopt data-driven HR decision-making: algorithm-based efficacy, data-driven efficacy, and users' competency-based self-efficacy.

A decisive aspect is **algorithm-based efficacy**, which encompasses users' expectations of the tool's performance. Study two emphasises that the *quality of the predictions* plays a significant role, as interviewees require a sufficient level of accuracy to consider the tool useful. However, the interviewees rated the prediction quality differently. In addition, the *traceability* of the results is also an important criterion for adoption. The results of the second study indicate that the transparency of the ML model and the ability to understand its decisions contribute to acceptance. In particular, the integration of *Explainable Artificial Intelligence* (XAI) is crucial to building trust in the complex and otherwise incomprehensible tool. *Practical applicability* is also highly relevant for the adoption process of data-driven decision-making. The study highlights that users pay attention to whether the tool is fully developed, how error-prone it is and whether it offers useful functions that enable efficient use.

In addition, **data-based efficacy** plays a significant role in the individual intention to adopt data-driven decision-making. As the results of the second study indicate, the acceptance of the tool is highly dependent on the *composition of the dataset* as well as the perceived *reliability* of the underlying data. While some interviewees rated the database as sufficient, others criticised the lack of or unrealistic nature of predictors for voluntary turnover. In addition, the perceived reliability of data management seems to be crucial for its use.

The **competency-based self-efficacy** refers to the level of confidence users feel in using the tool. Interviewees with *quantitative skills*, such as an analytical background and statistical knowledge, perceive it to be easier to interpret the different tools' outputs (for example, charts) and show greater interest in the information presented. Others rate the interpretation of the data or XAI charts as challenging and are less motivated to engage more intensively with the data. In addition, the findings of the second study emphasise that a certain amount of *HR-specific knowledge* is required to transfer the results of the tool into practice in a meaningful way.

Trust in the tool and underlying algorithms seem to be crucial, while transparent and explainable models particulary contribute to acceptance. Lyu and Wu (2025) confirm this finding by arguing that XAI plays a significant role in this acceptance process. This, in turn, leads to a higher algorithm-based efficacy, which leads to a higher intention to adopt. Organisations that want to encourage the adoption of data-driven HR decisions should therefore invest in these confidence-building measures, among others.

At the same time, the quality of the data exerts a major influence on the willingness to use a respective tool, as incomplete or unreliable information weakens the basis for decision-making. In this context, McCartney and Fu (2022a) highlight that the information technology used to store and provide data for data-driven decisions plays a key role in facilitating its adoption. Shet et al. (2021) confirm this finding by highlighting that the accessibility and availability of relevant data are critical for the adoption of HR Analytics.

It is also obvious that organisations need to develop a specific skillset within their employees to ensure that they are able to make sensitive data-driven decisions and fully exploit the benefits of such advanced tools, which is confirmed by the review of Alam et al. (2025). Gurusinghe et al. (2021) propose that the analytical competencies of HR professionals are positively related to adopting HR analytics. Harris et al. (2011) further highlight that a major obstacle to introducing analytics with HR data is the limited expertise in data analytics, statistics, and modelling among HR professionals. This skills gap hinders individuals and, consequently, the ability of organisations to interpret data effectively and gain actionable insights.

The individual intention to adopt data-driven HR decision-making is also limited by Normative Drivers, namely the legal framework and culture.

Participants in the second study report that the possible applications of the data-driven tool are severely restricted or not possible at all due to **legal requirements** as well as a strict interpretation of *data protection regulations*, particularly in the public sector. In addition, the *organisational councils* have far-reaching *co-determination rights* that extend beyond the legal requirements and enable employee representatives to stop decisions that affect the entire organisation. The interviewees, therefore, perceive that data-driven initiatives based on employee data were generally prevented. In addition to the legal framework, **organisational culture** seems to play an additional key role in the adoption of data-driven HR decision-making. It can be further distinguished between general *social norms* and the *organisation's internal culture.* The decision-making processes within the federal agency were often perceived by the interviewees in the study as irrational and time-consuming.

The results of the second study show that the adoption of data-driven HR decision-making processes is not only a question of technological readiness or strategic intent but is also significantly influenced by legal and cultural factors. Strict data protection regulations, such as those set out in the GDPR in the European context, along with far-reaching co-determination rights held by employee representatives can significantly restrict the introduction of such tools.

Beyond legal frameworks, deeply embedded social norms and cultural expectations within organisations also play a critical role in shaping the adoption process of tools for data-driven decision-making in HRM. For example, perceived uncertainty about the consequences of data usage and general resistance to organisational change prove to be obstacles. The findings of Bentvelzen et al. (2025) confirm that social influence is a relevant factor that determines the use of HR Analytics technology. Ultimately, the findings of study two illustrate that the successful introduction of data-driven HR tools requires not only technical solutions, but also careful navigation of the regulatory landscape, organisational culture and change management dynamics.

It is important to consider that the concept of normative drivers is defined in a relatively narrow sense in the second study. The analysis mainly takes specific social expectations or pressure from a limited group of stakeholders into account, namely the employee perspective of the examined federal agency. However, it needs to be acknowledged that additional forces such as competitive pressure from industry peer groups, market expectations, or influence of stakeholders, and the general public may also play a significant role in shaping the social norms (Fernandez and Gallardo-Gallardo 2021). These external influences, although not the central focus of this study, can exert considerable social pressure and warrant further exploration in future research (see also Bentvelzen et al. 2025).

The third study in this dissertation focuses on temporary managers who take HR decisions. By analysing the human capital and roles of temporary managers, the study provides insights into the human dimension of data-driven HR decision-making. These individuals, who are brought in for their expertise (especially in challenging times) and their outside perspective on organisations, serve as a particularly valuable lens. Temporary managers can be seen as human capital for decision-making as they bring new perspectives and a broad range of experiences to organisations. The study provides evidence that, based on their daily tasks, decision-making processes, and competency profiles, temporary managers can be divided into three different typologies: *The Decider*, *The Advisor* and *The Realiser.*

The Decider is characterised by strategic foresight, decisiveness, and a strong ethical compass, frequently leading high-stakes transformation initiatives that require clear and authoritative leadership. In contrast, *The Advisor* adopts a collaborative, coaching-oriented style, drawing on emotional intelligence to influence others through informal authority. *The Realiser* concentrates on operational implementation and pragmatic problem-solving, ensuring the execution of strategic intent at the process level.

The third study examined decision-making processes of the temporary manager, also encompassing the individual methods and frameworks used to collect, analyse, and apply data in HR decision-making. The interviews show that, at one end of the spectrum, this involves informal methods such as verbal data collection through communication or personal observations, which often lead to intuitive, less data-driven decisions. At the other end, it involves structured, data-supported approaches based on the deliberate selection of data sources, the use of analytical tools and technologies, and the systematic interpretation of results to guide HR decisions.

None of the three typologies – *The Decider, The Advisor,* and *The Realiser* – can be clearly positioned on a single spectrum in terms of the amount of data used for taking HR decisions. The type of data collection and use by the temporary managers seems to depend on the respective situation and organisational circumstances, such as the availability and reliability of data. However, there are strong tendencies regarding the groups of people (management level, employees, and external parties) with whom communication takes place to gather information. Decision-making is often based on a combination of verbal information, observations and data analysis. Temporary managers often strive to base their decisions on data or, at the very least, incorporate data into their decision-making processes. They state that they use strategic management tools such as reports, KPIs, dashboards, and benchmarks, as well as IT tools such as *SAP SuccessFactor* and, in some cases, AI applications.

Overall, the interviews indicate that *The Realiser* attempts to operate in a more data-driven manner. This may also be related to the tasks of this typology of temporary manager, who sets up or further develops planning and reporting systems to effectively manage and control the organisation in the long term. To this end, they pursue creative and pragmatic approaches to data collection and often take an experimental approach to making processes measurable.

By identifying three typologies – *The Decider, The Advisor* and *The Realiser* – the third study of this dissertation emphasises that taking HR decisions is not only influenced by organisational circumstances and technological conditions, but fundamentally by the **individual characteristics, values and approaches** of those who make them (Vargas et al. 2018). Each (temporary) manager has a unique combination of thinking patterns, attitudes and leadership styles. They draw on different types of information and data in different situations, such as observations, information from conversations and data analyses. This underscores the importance of the human perspective, as decision-makers do not simply apply data passively; but actively interpret, filter, and contextualise it based on their own professional identities and situational judgement. This shows that data-driven HR decision-making is not purely a technical or structural challenge, but rather a human-centred process that is strongly influenced by individuals such as a temporarily employed manager. These findings underscore the heterogeneity of decision-makers in terms of their style, skills and approach to data. The study by Bentvelzen et al. (2025) emphasises the existence of heterogeneous users in relation to HR Analytics technologies. Differences were observed in how users evaluate the performance benefits and user-friendliness of the tools, the extent of social influence, and the availability of organisational and technical infrastructure supporting their application. The authors identified four different user profiles: *Enthusiasts*, *Optimists*, *Optimistic Strugglers*, and *Sceptic Diplomats*.

Additionally, these findings of study three suggest that data-driven HR decision-making efforts should **consider the various human roles and capacities** involved in decision-making. Fostering data-driven HR decision-making and cultures requires effective support for reflective, adaptable, and context-sensitive human engagement with data. In this context, the study by Bentvelzen et al. (2025) further concludes that among the four identified user groups, *Enthusiasts* appear to be the most satisfied and actively engaged users. Their consistently positive evaluations of the advanced technology are closely related to higher levels of satisfaction, more frequent use, and more comprehensive exploitation of the technology's capabilities. This suggests that organisations can significantly improve both the acceptance and effective adoption of advanced HR technologies by recognising and taking into account the different needs and attitudes of the various user groups.

Overall, the adoption of data-driven HR decision-making appears to be uniquely shaped by individuals as they possess a distinct combination of human thinking patterns, salient beliefs, and experiences. It is this human dimension involving curiosity, openness to change, and strategic leadership that ultimately determine whether data becomes a tool for insight or remains unrealised potential.

5.4 Interrelation between Technological and Human Perspectives

The findings of this dissertation also underline that the three perspectives cannot be viewed in isolation from one another. The second study in particular highlights the deep interrelationships between the technological and human perspectives on ML tools. Therefore, this section is dedicated to discussing its specific findings.

The second study of this thesis indicates that the various characteristics of tools for data-driven HR decision-making, in the specific case of an ML tool, affect the behavioural beliefs of individuals and thus can play a decisive role in the adoption process. Thus, the opportunity to test a tool in advance (trialability) shows a positive effect on attitudes towards the technology. Furthermore, the degree of automation appears to influence the attitude and PBC of potential users, as they must choose between automation and augmentation. The transparency of a tool is a further key aspect that not only affects attitude, but also the PBC over the technology. In addition, study two reveals that self-learning capabilities of a tool can increase the PBC, but can also raise concerns about a lack of control.

The findings of Vargas et al. (2018) confirm that **trialability** plays an essential role for individuals in the adoption of advanced analytics in HR decision-making, while the results of Obeidat (2012) observe trialability to be the most significant predictor for the individual adoption of HRIS.

Study two's results related to the degree of automation are consistent with the findings of Dietvorst et al. (2018), who observed a pronounced aversion of users to fully **automated** predictive analytics tools, an aversion that declines when users are granted even minimal control over the decision-making process. Furthermore, Hofeditz et al. (2022) advocate that humans should take final hiring decisions, but that AI recommendations can reduce discrimination in hiring decisions. These insights collectively highlight the importance of maintaining human control in automated tools in order to strengthen both user trust and fairness.

The results regarding **transparency** are supported by the studies related to XAI conducted by Kim et al. (2023) and Haque et al. (2023), which emphasise the significant role that visualisations play in enhancing user comprehension and promoting system adoption. Diefenhardt et al. (2024) argue similarly, emphasising that visualisation can transmit analytic results and help gain stakeholders' recognition. This emphasises the value of transparent and interpretable outputs from advanced analytics in driving user engagement and trust.

The study by Berger et al. (2021) reveals that users honour an **algorithm's ability to learn** and thus supports the findings of study two. Their study participants relied more on the learning than on the non-learning algorithmic advisor in their incentivised estimation. This suggests that an algorithm's self-learning capabilities are a promising countermeasure against the reluctance or unwillingness of people to use algorithms (Berger et al. 2021).

Although **fairness** is a central ethical principle, it is not always actively incorporated into decision-making in practice. The findings of the second study are alarming as the interviewees do not prominently raise fairness-related concerns. Overall, the study reveals no evidence that the unequal treatment of gender or age groups affected the interviewees' intention to adopt the data-driven HR tool. With the same contextual focus on the early adoption of advanced analytics in the public sector, Neumann et al. (2024) report similar findings regarding fairness in their study. They point out that AI adoption at a low maturity level is characterised by an emphasis on promising business cases, a strong dependence on external partners, the use of change management to foster acceptance, and minimal attention to ethical aspects such as algorithmic accountability and fairness (Neumann et al. 2024). It is therefore apparent that practical considerations regarding adoption often take precedence over ethical considerations, which may explain the absence of a discourse on fairness among the respondents. Organisations therefore require proactive measures to ensure fairness in the long term and promote acceptance of the tool. The establishment of internal guidelines and approval mechanisms, supported by internal or external expertise, is therefore highly recommended to ensure the responsible adoption and use of the tools. HR managers also need a sound understanding of how the tools are structured and how they function to ensure fair and informed use. Training and targeted continuing education play an important role, particularly in understanding the limitations of the tool. A lack of technical understanding can be a barrier to acceptance, especially for users without advanced analytics expertise. Therefore, clear explanations are needed to inform users about how the tools work and on what basis they make decisions.

5.5 Recommendations for Organisations

The comprehensive discussion of this dissertation is concluded with considerations for practice. The aim of this section is therefore to propose practical measures that can be used to address the key challenges in order to holistically encourage the effective adoption of data-driven HR decision-making in organisations. Targeted recommendations are provided drawing on the findings of this dissertation, further-reaching considerations, and insights from current literature. The recommendations can be divided into five key groups:

(1) fostering a data-driven culture,

(2) developing a digital strategy,

(3) providing expertise,

(4) providing appropriate IT infrastructure, and

(5) establishing a governance system.

To effectively **foster a data-driven culture** that supports the adoption of data-driven HR decision-making, organisations should take a multi-level, integrated approach that combines leadership support, strengthens the position of the HR department, cross-functional collaborative structure, user empowerment, and strategic communication measures:

- **Cultivate a data-driven culture through leadership:** Senior management plays an active role in championing data-based practices by fostering a data-driven decision-making culture. Therefore, senior management should create an organisational climate of experimentation and learning, especially in the early stages of cultural transformation, by encouraging innovation and normalising mistakes as part of the learning process (Ulrich and Dulebohn 2015; Levenson 2018; Karwehl and Kauffeld 2021). Gurusinghe et al. 2021 argue that a data-driven culture acts as a moderating construct in pushing organisations to improve their HR analytics maturity stage.
- **Involvement of the HR department:** The position of HR managers should be reshaped and strengthened through the support of senior management, whereby advanced data-driven approaches and technologies should not only be seen as the responsibility of the IT department, but as part of and authority of HR itself (Wirges and Neyer 2023). The scope of responsibility of HR managers needs to be clearly defined (Wirges and Neyer 2023), while their positions could be strengthened by including HR in the leadership team of data-driven initiatives and through the development of data-related skills with the help of training.
- **Promote collaboration:** Effective adoption and use of data-driven approaches in HR requires overcoming the silo mentality (Angrave et al. 2016) and fostering strong collaboration between departments (Shet et al. 2021; Wirges and Neyer 2023). Regular coordination meetings between the involved interdisciplinary departments can build efficient communication channels, while IT teams should actively co-develop HR data governance frameworks and align themselves with strategic organisational goals (e.g. McCartney and Fu 2022b).
- **Encourage peer learning:** A peer support structure can serve as both a learning resource and a means of internal advocacy. Establishing user forums or Q&A platforms can create communities of practice where employees share experiences, ask questions, and influence each other socially while increasing engagement and adoption (Bentvelzen et al. 2025).

- **Targeted communication:** Organisations should adjust their communication strategies to different adoption phases and employee attitudes (Coolen et al. 2023). Active communication can address upcoming concerns more effectively, build trust, and foster smoother transitions.

Secondly, organisations should **develop a digital strategy** that strengthens data-driven HR decision-making. It should be aligned with the general organisational objectives and be supported by appropriately selected projects and the incorporation of new developments:

- **Develop a digital HRM strategy:** Organisations should develop an integrated and holistic digital HRM strategy (Nankervis and Cameron 2023), while the strategic HR objectives set by the senior management should be aligned with the organisation's long-term strategy. This connects the strategic orientation of HR with the company's long-term goals, which strengthens the long-term support of the initiatives.

- **Start small initiatives with practical value:** Organisations should initially start with small, targeted projects to demonstrate their practical value (Rasmussen and Ulrich 2015; Boudreau and Cascio 2017; Desouza et al. 2020; Neumann et al. 2024; Diefenhardt et al. 2024) while minimising risk and resistance as these pilot projects can build acceptance and drive cultural change. Over time, these smaller initiatives can scale into more comprehensive practices supported by growing internal capability and confidence.

- **Monitor continuous developments:** Successful adoption and use of data-driven HR decision-making requires ongoing alignment with business dynamics and technological developments. Industry trends and developments of tools and methodologies, as well as legal conditions, should be monitored accordingly (Alam et al. 2025) to update the approaches and communicate accordingly with different stakeholders. The responsible employees should get actively engaged in forums, conferences and other exchange platforms and keep up to date with the latest developments.

Third, to ensure successful adoption and sustained use of data-driven HR decision-making, organisations must invest in **building** both **internal capabilities and external support structures**:

- **Build internal expertise:** Organisations need to build internal expertise to effectively adopt and apply data-driven HR decision-making through tailored training and learning formats. The study by Pan et al. (2022) underlines this by showing that technology competencies encourage AI adoption. HR professionals need to develop an understanding of the methods and the data sources as well as what the data means and how it aligns with the organisation's strategic plan (Vargas et al. 2018). Structured training programs for IT employees and HR professionals can include video tutorials, hands-on workshops, and interactive learning resources (Aguinis et al. 2024; Bentvelzen et al. 2025). Moreover, mentoring or coaching programs that connect HR professionals with managers or executives from other business functions can broaden perspectives and encourage cross-functional analytical thinking (Alam et al. 2025).

- **Leverage external expertise:** In addition to building internal capabilities, organisations should actively engage with external sources of expertise. Collaborating with consultants, data scientists, and academic institutions can accelerate the development of high-impact data-driven decision-making (Levenson 2018; Coolen et al. 2023; Nankervis and Cameron 2023; Neumann et al. 2024). These partnerships can not only expand the organisation's technical capacity but also ensure access to advanced methods and broader professional networks that can support long-term learning and innovation.

Fourth, a modern and well-integrated **IT infrastructure** is fundamental for the successful adoption of data-driven decision-making in HRM. Adequate systems and tools, a focus on usability, and strong governance are necessary components:

- **Invest strategically in digital infrastructure:** In addition to budgets for skilled professionals and training, organisations need to make substantial investments in the digital transformation of HRM, including hardware and software. Organisations should critically examine which technologies are best suited for the intended purposes and to what extent existing systems are compatible. Additionally, organisations can face profound challenges in terms of functionality and collecting, cleaning and deploying the data (Angrave et al. 2016; Desouza et al. 2020). The HR database increasingly originates from diverse technologies such as Data Lakes and Cloud-based Platforms, and sources, for example, traditional HRIS or ERP systems. Data can range from multiple systems across departments (Marler and Boudreau 2017). A modern and well-integrated digital infrastructure is therefore essential for the adoption of data-driven HR decision-making. Organisations should pay particular attention to this and act thoughtfully.

- **Ensure usability of the tools:** The findings of study two reveal that the ease of use is a critical condition for successful adoption of data-driven HR decision-making. Organisations should select and design tools with intuitive interfaces and user-friendly features to lower the entry barrier for HR professionals and other users. Ensuring usability also means involving the end-users in the evaluation of new tools and soliciting their feedback to optimise the user experience.
- **Prioritise data privacy and security in infrastructure:** As data becomes central to HR decision-making, the risks associated with its misuse or violation also increase. A committee of HR, IT, and legal teams should collaborate to establish clear data management processes and infrastructure that address data privacy, access control, and compliance requirements. Effective data governance frameworks might help to mitigate these risks (see e.g. Harris et al. 2011; Marler and Boudreau 2017; Bannister and Connolly 2020) and build trust in the tool across the organisation. Furthermore, clear responsibilities need to be set with no gaps in the accountability chain (Bannister and Connolly 2020).

Ultimately, the adoption of data-driven technologies such as ML in HR decision-making carries a great deal of potential; but it also poses substantial ethical, legal, and operational risks. A **clearly defined governance system** is therefore essential to ensure appropriate data quality standards and data protection mechanisms, as well as the responsible use:

- **Strengthen the role of IT in governance development:** As they are the most suitable department within the organisation for this task, IT departments must be aware of their responsibility for developing and enforcing data governance frameworks. This includes defining data quality standards and building privacy mechanisms into systems. Senior management should explicitly empower them to do so.
- **Implement clear guidelines for responsible use:** Findings from the first and second studies highlight the need for governance structures that ensure ethical and non-discriminatory use of data-driven decision-making tools. Bannister and Connolly (2020) emphasise that when using advanced technologies, it is not just a matter of machines making mistakes; but rather that values, prejudices, and biases are embedded in them, which can lead to discrimination. Further, the study by Pan et al. (2022) demonstrates that regulatory support encourages AI adoption. Organisations should commission diverse teams to develop clear guidelines. Regulatory requirements, such as laws and best practices from professional groups, should also be taken into account.

- **Act transparent regarding data use:** To foster employee trust and uphold ethical data practices, organisations should prioritise transparency and maintain open, ongoing communication about how employee data is collected, used, and protected (McCartney and Fu 2022b; Lyu and Wu 2025). Such efforts not only enhance trust but also help break down barriers between employees and management.

Figure 15 summarises the concrete measures recommended. These specific measures can contribute to the successful adoption of data-driven HR decision-making by laying a strategic foundation. However, given the dynamic nature of organisations and the complexity of data-driven approaches, complementary measures can equally support the process. Moreover, continuous adjustments may be necessary throughout the adoption process in order to respond to changing organisational needs, technological advancements, and emerging insights. This would ensure the long-term effectiveness and adaptability of the data-driven decision-making initiatives.

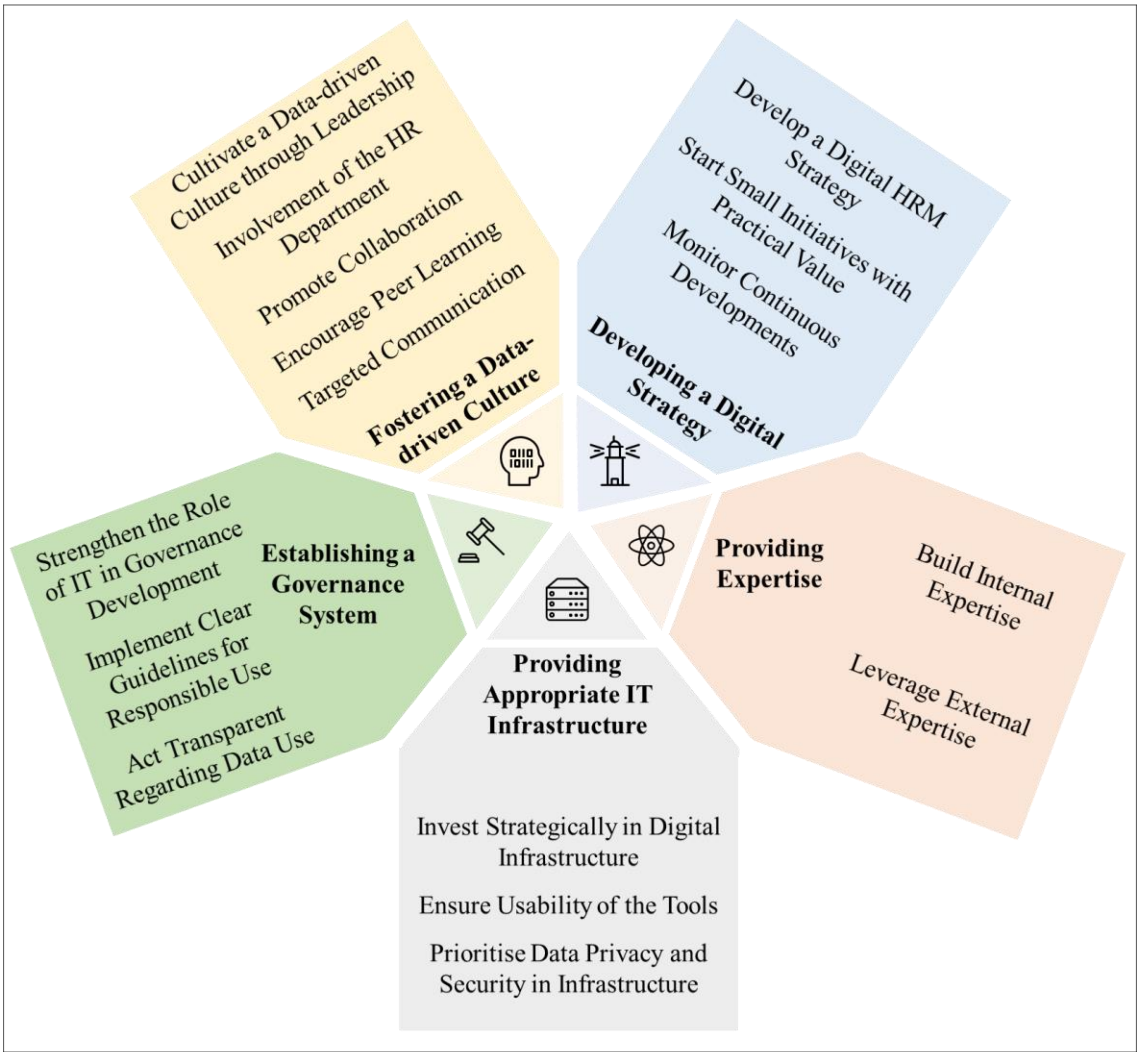

Figure 15: Recommended measures to support the adoption of data-driven HR decision-making

5.6 Conclusion

This dissertation emphasises that the effective adoption of data-driven HR decision-making across different stages of analytics maturity requires a multidimensional transformation, involving an integrated and supportive organisational culture and structure, the salient beliefs and thinking patterns of individuals, as well as robust technological foundations. It emphasises the multifaceted nature of adopting data-driven HR decision-making in terms of possible areas of application, deployable technologies and organisational challenges, and highlights the need for a holistic approach. From an organisational perspective, it is necessary to foster a culture that values data, develop data literacy among employees, support cross-functional collaboration, and establish strict governance frameworks. On the human side, addressing individual decision-making processes as well as employee concerns about data privacy and ethics are vital to building trust and acceptance. From a technological perspective, robust infrastructure, reliable data sources, and user-friendly tools are important prerequisites. Overall, this dissertation empirically highlights that data-driven HR decision-making is not a universally applicable solution. It requires tailored efforts on the part of the organisation. Ultimately, the effectiveness of data-driven HRM depends on how well the technology, organisation, and human dimensions are balanced and continuously adapted to evolving organisational needs and societal expectations in order to leverage the potential of evidence-based decisions for the benefit of employees.

5.7 List of References

Aguinis, Herman; Beltran, Jose R.; Cope, Amando (2024): How to Use Generative AI as a Human Resource Management Assistant. In: Organizational Dynamics 53 (1), p. 101029. DOI: 10.1016/j.orgdyn.2024.101029.

Ajzen, Icek (1991): The Theory of Planned Behavior. In: Organizational Behavior and Human Decision Processes 50 (2), pp. 179–211. DOI: 10.1016/0749-5978(91)90020-t.

Alam, Shafiq; Dong, Zhan; Kularatne, Zhan; Rashid, Muhammad S. (2025): Exploring Approaches to Overcome Challenges in Adopting Human Resource Analytics through Stakeholder Engagement. In: Management Review Quarterly. DOI: 10.1007/s11301-025-00491-y.

Alon-Barkat, Saar; Busuioc, Madalina (2023): Human–AI Interactions in Public Sector Decision Making: “Automation Bias” and “Selective Adherence” to Algorithmic Advice. In: Journal of Public Administration Research and Theory 33 (1), pp. 153–169. DOI: 10.1093/jopart/muac007.

Angrave, David; Charlwood, Andy; Kirkpatrick, Ian; Lawrence, Mark; Stuart, Mark (2016): HR and Analytics: Why HR Is Set to Fail the Big Data Challenge. In: Human Resource Management Journal 26 (1), pp. 1–11. DOI: 10.1111/1748-8583.12090.

Apley, Daniel W.; Zhu, Jingyu (2020): Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models. In: Journal of the Royal Statistical Society: Series B (Statistical Methodology) 82 (4), pp. 1059–1086. DOI: 10.1111/rssb.12377.

Arrieta, Alejandro B.; Díaz-Rodríguez, Natalia; Del Ser, Javier; Bennetot, Adrien; Tabik, Siham; Barbado, Alberto; Garcia, Salvador; Gil-Lopez, Sergio; Molina, Daniel; Benjamins, Richard; Chatila, Raja; Herrera, Francisco (2020): Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. In: Information Fusion 58, pp. 82–115. DOI: 10.1016/j.inffus.2019.12.012.

Bannister, Frank; Connolly, Regina (2020): Administration by Algorithm: A Risk Management Framework. In: Information Polity 25 (4), pp. 471–490. DOI: 10.3233/IP-200249.

Bentvelzen, Margriet; Boon, Corine; Den Hartog, Deanne N. (2025): A Person-Centered Approach to Individual People Analytics Adoption. In: Journal of Organizational Effectiveness: People and Performance 12 (5), pp. 60–82. DOI: 10.1108/JOEPP-07-2023-0276.

Berger, Benedikt; Adam, Martin; Rühr, Alexander; Benlian, Alexander (2021): Watch Me Improve – Algorithm Aversion and Demonstrating the Ability to Learn. In: Business & Information Systems Engineering 63 (1), pp. 55–68. DOI: 10.1007/s12599-020-00678-5.

Boudreau, John; Cascio, Wayne (2017): Human Capital Analytics: Why Are We Not There? In: Journal of Organizational Effectiveness: People and Performance 4 (2), pp. 119–126. DOI: 10.1108/JOEPP-03-2017-0021.

Chatterjee, Sheshadri; Rana, Nripendra P.; Dwivedi, Yogesh K.; Baabdullah, Abdullah M. (2021): Understanding AI Adoption in Manufacturing and Production Firms Using an Integrated TAM-TOE Model. In: Technological Forecasting and Social Change 170, p. 120880. DOI: 10.1016/j.techfore.2021.120880.

Choudhury, Prithwiraj; Allen, Ryan T.; Endres, Michael G. (2021): Machine Learning for Pattern Discovery in Management Research. In: Strategic Management Journal 42 (1), pp. 30–57. DOI: 10.1002/smj.3215.

Chowdhury, Soumyadeb; Budhwar, Pawan; Dey, Prasanta K.; Joel-Edgar, Sian; Abadie, Amelie (2022): AI-Employee Collaboration and Business Performance: Integrating Knowledge-based View, Socio-technical Systems and Organisational Socialisation Framework. In: Journal of Business Research 144, pp. 31–49. DOI: 10.1016/j.jbusres.2022.01.069.

Chowdhury, Soumyadeb; Dey, Prasanta K.; Joel-Edgar, Sian; Bhattacharya, Sudeshna; Rodriguez-Espindola, Oscar; Abadie, Amelie; Truong, Linh (2023a): Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework. In: Human Resource Management Review 33 (1), p. 100899. DOI: 10.1016/j.hrmr.2022.100899.

Chowdhury, Soumyadeb; Joel-Edgar, Sian; Dey, Prasanta Kumar; Bhattacharya, Sudeshna; Kharlamov, Alexander (2023b): Embedding Transparency in Artificial Intelligence Machine Learning Models: Managerial Implications on Predicting and Explaining Employee Turnover. In: The International Journal of Human Resource Management 34 (14), pp. 1–32. DOI: 10.1080/09585192.2022.2066981.

Coolen, Patrick; van den Heuvel, Sjoerd; van de Voorde, Karina; Paauwe, Jaap (2023): Understanding the Adoption and Institutionalization of Workforce Analytics: A Systematic Literature Review and Research Agenda. In: Human Resource Management Review 33 (4), p. 100985. DOI: 10.1016/j.hrmr.2023.100985.

Dastin, Jeffrey (2022): Amazon Scraps Secret AI Recruiting Tool that Showed Bias Against Women. In: Martin, Kirsten (Ed.): Ethics of Data and Analytics. Boca Raton, Florida: Auerbach Publications, pp. 296–299. DOI: 10.1201/9781003278290-44.

Desouza, Kevin C.; Dawson, Gregory S.; Chenok, Daniel (2020): Designing, Developing, and Deploying Artificial Intelligence Systems: Lessons from and for the Public Sector. In: Business Horizons 63 (2), pp. 205–213. DOI: 10.1016/j.bushor.2019.11.004.

Diefenhardt, Felix; Rapp, Marco L.; Bader, Verena; Mayrhofer, Wolfgang (2024): 'In God We Trust. All Others Must Bring Data': Unpacking the Influence of Human Resource Analytics on the Strategic Recognition of Human Resource Management. In: Human Resource Management Journal. DOI: 10.1111/1748-8583.12583.

Dietvorst, Berkeley J.; Simmons, Joseph P.; Massey, Cade (2018): Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. In: Management Science 64 (3), pp. 1155–1170. DOI: 10.1287/mnsc.2016.2643.

Edwards, Martin R.; Charlwood, Andy; Guenole, Nigel; Marler, Janet (2022): HR Analytics: An Emerging Field Finding Its Place in the World alongside Simmering Ethical Challenges. In: Human Resource Management Journal 34 (2), pp. 326–336. DOI: 10.1111/1748-8583.12435.

Fernandez, Vicenc; Gallardo-Gallardo, Eva (2021): Tackling the HR Digitalization Challenge: Key Factors and Barriers to HR Analytics Adoption. In: Competitiveness Review 31 (1), pp. 162–187. DOI: 10.1108/CR-12-2019-0163.

Fredriksson, Magnus; Pallas, Josef (2016): Characteristics of Public Sectors and Their Consequences for Strategic Communication 10 (3), pp. 149–152. DOI: 10.1080/1553118X.2016.1176572.

Gurusinghe, R. Navodya; Arachchige, Bhadra J. H.; Dayarathna, Dushar (2021): Predictive HR Analytics and Talent Management: A Conceptual Framework. In: Journal of Management Analytics 8 (2), pp. 195–221. DOI: 10.1080/23270012.2021.1899857.

Haque, A. K. M. Bahalul; Islam, A. K. M. Najmul; Mikalef, Patrick (2023): Explainable Artificial Intelligence (XAI) from a User Perspective. A Synthesis of Prior Literature and Problematizing Avenues for Future Research. In: Technological Forecasting and Social Change 186, p. 122120. DOI: 10.1016/j. techfore.2022.122120.

Harris, Jeanne G.; Craig, Elizabeth; Light, David A. (2011): Talent and Analytics: New Approaches, Higher ROI. In: Journal of Business Strategy 32 (6), pp. 4–13. DOI: 10.1108/02756661111180087.

van den Heuvel, Sjoerd; Bondarouk, Tanya (2017): The Rise (and Fall?) of HR Analytics: A Study into the Future Application, Value, Structure, and System Support. In: Journal of Organizational Effectiveness: People and Performance 4 (2), pp. 157–187. DOI: 10.1108/JOEPP-03-2017-0022.

Highhouse, Scott (2008): Stubborn Reliance on Intuition and Subjectivity in Employee Selection. In: Industrial and Organizational Psychology 1 (3), pp. 333–342. DOI: 10.1111/j.1754-9434.2008.00058.x.

Hofeditz, Lennart; Clausen, Sünje; Rieß, Alexander; Mirbabaie, Milad; Stieglitz, Stefan (2022): Applying XAI to an AI-Based System for Candidate Management to Mitigate Bias and Discrimination in Hiring. In: Electronic Markets 32 (4), pp. 2207–2233. DOI: 10.1007/s12525-022-00600-9.

Holtom, Brooks C.; Mitchell, Terence R.; Lee, Thomas W.; Eberly, Marion B. (2008): 5 Turnover and Retention Research: A Glance at the Past, a Closer Review of the Present, and a Venture into the Future. In: Academy of Management Annals 2 (1), pp. 231–274. DOI: 10.1080/19416520802211552.

Hom, Peter W.; Lee, Thomas W.; Shaw, Jason D.; Hausknecht, John P. (2017): One Hundred Years of Employee Turnover Theory and Research. In: Journal of Applied Psychology 102 (3), pp. 530–545. DOI: 10.1037/apl0000103.

Karwehl, Laura J.; Kauffeld, Simone (2021): Traditional and New Ways in Competence Management: Application of HR Analytics in Competence Management. In: Gruppe Interaktion Organisation Zeitschrift für Angewandte Organisationspsychologie 52 (1), pp. 7–24. DOI: 10.1007/s11612-021-00548-y.

Kim, Doha; Song, Yeosol; Kim, Songyie; Lee, Sewang; Wu, Yanqin; Shin, Jungwoo; Lee, Daeho (2023): How Should the Results of Artificial Intelligence Be Explained to Users? – Research on Consumer Preferences in User-Centered Explainable Artificial Intelligence. In: Technological Forecasting and Social Change 188, p. 122343. DOI: 10.1016/j.techfore.2023.122343.

Levenson, Alec (2018): Using Workforce Analytics to Improve Strategy Execution: Using Workforce Analytics to Improve Strategy Execution. In: Human Resource Management 57 (3), pp. 685–700. DOI: 10.1002/hrm.21850.

Lodato, Michael A.; Highhouse, Scott; Brooks, Margaret E. (2011): Predicting Professional Preferences for Intuition-Based Hiring. In: Journal of Managerial Psychology 26 (5), pp. 352–365. DOI: 10.1108/02683941111138985.

Lyu, Qi; Wu, Shaomin (2025): Explainable Artificial Intelligence for Business and Economics: Methods, Applications and Challenges. In: Expert Systems 42 (4). DOI: 10.1111/exsy.70017.

Makarius, Erin E.; Mukherjee, Debmalya; Fox, Joseph D.; Fox, Alexa K. (2020): Rising with the Machines: A Sociotechnical Framework for Bringing Artificial Intelligence into the Organization. In: Journal of Business Research 120, pp. 262–273. DOI: 10.1016/j.jbusres.2020.07.045.

Margetts, Helen; Dorobantu, Cosmina (2019): Rethink Government with AI. In: Nature 568 (7751), pp. 163–165. DOI: 10.1038/d41586-019-01099-5.

Margherita, Alessandro (2022): Human Resources Analytics: A Systematization of Research Topics and Directions for Future Research. In: Human Resource Management Review 32 (2), p. 100795. DOI: 10.1016/j.hrmr.2020.100795.

Marler, Janet H.; Boudreau, John W. (2017): An Evidence-based Review of HR Analytics. In: The International Journal of Human Resource Management 28 (1), pp. 3–26. DOI: 10.1080/09585192.2016.1244699.

McCartney, Steven; Fu, Na (2022a): Bridging the Gap: Why, How and When HR Analytics Can Impact Organizational Performance. In: Management Decision 60 (13), pp. 25–47. DOI: 10.1108/MD-12-2020-1581.

McCartney, Steven; Fu, Na (2022b): Promise versus Reality: A Systematic Review of the Ongoing Debates in People Analytics. In: Journal of Organizational Effectiveness 9 (2), pp. 281–311. DOI: 10.1108/JOEPP-01-2021-0013.

Mikalef, Patrick; Krogstie, John (2020): Examining the Interplay between Big Data Analytics and Contextual Factors in Driving Process Innovation Capabilities. In: European Journal of Information Systems 29 (3), pp. 260–287. DOI: 10.1080/0960085x.2020.1740618.

Mikalef, Patrick; Lemmer, Kristina; Schaefer, Cindy; Ylinen, Maija; Fjørtoft, Siw Olsen; Torvatn, Hans Y.; Gupta, Manjul; Niehaves, Bjoern (2022): Enabling AI Capabilities in Government Agencies: A Study of Determinants for European Municipalities. In: Government Information Quarterly 39 (4), p. 101596. DOI: 10.1016/j.giq.2021.101596.

Miles, Andrew; Sadler-Smith, Eugene (2014): "With Recruitment I Always Feel I Need to Listen to My Gut": The Role of Intuition in Employee Selection. In: Personnel Review 43 (4), pp. 606–627. DOI: 10.1108/PR-04-2013-0065.

Min, Hokey (2021): Business Analytics Practices and Managerial Implications Based on the Evidence from Korea. In: American Journal of Business 36 (2), pp. 150–168. DOI: 10.1108/ajb-05-2020-0066.

Molnar, Christoph (2022): Interpretable Machine Learning – A Guide for Making Black Box Models Interpretable. 2. Edition. Morisville, North Carolina: Lulu.

Nam, Dalwoo; Lee, Junyeong; Lee, Heeseok (2019): Business Analytics Adoption Process: An Innovation Diffusion Perspective. In: International Journal of Information Management 49, pp. 411–423. DOI: 10.1016/j.ijinfomgt.2019.07.017.

Nankervis, Alan R.; Cameron, Roslyn (2023): Capabilities and Competencies for Digitised Human Resource Management: Perspectives from Australian HR Professionals. In: Asia Pacific Journal of Human Resources 61 (1), pp. 232–251. DOI: 10.1111/1744-7941.12354.

Neumann, Oliver; Guirguis, Katharina; Steiner, Reto (2024): Exploring Artificial Intelligence Adoption in Public Organizations: A Comparative Case Study. In: Public Management Review 26 (1), pp. 114–141. DOI: 10.1080/14719037.2022.2048685.

Obeidat, Bader Y. (2012): The Relationship between Innovation Diffusion and Human Resource Information Systems (HRIS). In: Perspectives of Innovation in Economics and Business (PIEB) 12 (3), pp. 41–58. Available online at: https://ideas.repec.org/a/pdc/jrpieb/v12y2012i3p41-58.html (retrieved on July 7, 2025).

Oswald, Frederick L.; Behrend, Tara S.; Putka, Dan J.; Sinar, Evan (2020): Big Data in Industrial-Organizational Psychology and Human Resource Management: Forward Progress for Organizational Research and Practice. In: Annual Review of Organizational Psychology and Organizational Behavior 7, pp. 505–533. DOI: 10.1146/annurev-orgpsych-032117-104553.

Pan, Yuan; Froese, Fabian; Liu, Ni; Hu, Yunyang; Ye, Maolin (2022). The Adoption of Artificial Intelligence in Employee Recruitment: The Influence of Contextual Factors. In: International Journal of Human Resource Management 33 (6), pp. 1125–1147. DOI: 10.1080/09585192.2021.1879206.

Pumplun, Luisa; Tauchert, Christoph; Heidt, Margareta (2019): A New Organizational Chassis for Artificial Intelligence – Exploring Organizational Readiness Factors. In: ECIS 2019 Proceedings. Stockholm, Uppsala: Association for Information Systems. Available online at: https://aisel.aisnet.org/ecis2019_rp/106 (retrieved on July 7, 2025).

Rai, Arun (2020): Explainable AI: From Black Box to Glass Box. In: Journal of the Academy of Marketing Science 48 (1), pp. 137–141. DOI: 10.1007/s11747-019-00710-5.

Raschka, Sebastian (2018): Model Evaluation, Model Selection, and Algorithm Selection in Machine Learning. Available online at: http://arxiv.org/pdf/1811.12808 (retrieved on July 7, 2025).

Rasmussen, Thomas; Ulrich, Dave (2015): Learning from Practice: How HR Analytics Avoids Being a Management Fad. In: Organizational Dynamics 44 (3), pp. 236–242. DOI: 10.1016/j.orgdyn.2015.05.008.

Richter, Peter (2012): Die Organisation öffentlicher Verwaltung. In: Apelt, Tacke (Ed.): Handbuch Organisationstypen. Wiesbaden: Springer, pp. 91–112. DOI: 10.1007/978-3-531-93312-2_5.

Rombaut, Evy; Guerry, Marie-Anne (2018): Predicting Voluntary Turnover through Human Resources Database Analysis. In: Management Research Review 41 (1), pp. 96–112. DOI: 10.1108/MRR-04-2017-0098.

Satell, Greg; Sutton, Josh (2019): We Need AI That Is Explainable, Auditable and Transparent. In: Harvard Business Review. Available online at: https://tinyurl.com/s5pyn7a (retrieved on July 7, 2025).

Schaefer, Cindy; Lemmer, Kristina; Samy Kret, Kret; Ylinen, Maija; Mikalef, Patrick; Niehaves, Bjoern (2021): ”Truth or Dare?” – How Can We Influence the Adoption of Artificial Intelligence in Municipalities? In: Proceedings of the 54th Hawaii International Conference on System Sciences, pp. 2347–2356. Maui, Hawaii.

Shet, Sateesh V.; Poddar, Tanuj; Wamba Samuel, Fosso; Dwivedi, Yogesh K. (2021): Examining the Determinants of Successful Adoption of Data Analytics in Human Resource Management – A Framework for Implications. In: Journal of Business Research 131 (C), pp. 311–326. DOI: 10.1016/j.jbusres.2021.03.054.

Shin, Donghee; Park, Yong J. (2019): Role of Fairness, Accountability, and Transparency in Algorithmic Affordance. In: Computers in Human Behavior 98, pp. 277–284. DOI: 10.1016/j.chb.2019.04.019.

Speer, Andrew B. (2021): Empirical Attrition Modelling and Discrimination: Balancing Validity and Group Differences. In: Human Resource Management Journal 34 (1), pp. 1–19. DOI: 10.1111/1748-8583.12355.

Srivastava, Sonalee; Bajaj, Badri; Dev, Santosh (2020): Human Resource Information System Adoption and Implementation Factors. In: International Journal of Human Capital and Information Technology Professionals 11 (4), pp. 80–98. DOI: 10.4018/IJHCITP.2020100105.

Ulrich, Dave; Dulebohn, James H. (2015): Are We There Yet? What’s Next for HR? In: Human Resource Management Review 25 (2), pp. 188–204. DOI: 10.1016/j.hrmr.2015.01.004.

Vargas, Roslyn; Yurova, Yuliya V.; Ruppel, Cynthia P.; Tworoger, Leslie C.; Greenwood, Regina (2018): Individual Adoption of HR Analytics: A Fine Grained View of the Early Stages Leading to Adoption. In: The International Journal of Human Resource Management 29 (22), pp. 3046–3067. DOI: 10.1080/09585192.2018.1446181.

Wirges, Felix; Neyer, Anne-Katrin (2023): Towards a Process-Oriented Understanding of HR Analytics: Implementation and Application. In: Review of Managerial Science 17 (6), pp. 2077–2108. DOI: 10.1007/s11846-022-00574-0.

Xu, Jinying; Lu, Weisheng (2022): Developing a Human-Organization-Technology Fit Model for Information Technology Adoption in Organizations. In: Technology in Society 70, p. 102010. DOI: 10.1016/j.techsoc.2022.102010.

Yusof, Maryati Mohd; Kuljis, Jasna; Papazafeiropoulou, Anastasia; Stergioulas, Lampros K. (2008): An Evaluation Framework for Health Information Systems: Human, Organization and Technology-Fit Factors (HOT-fit). In: International Journal of Medical Informatics 77, pp. 386–398. DOI: 10.1016/j.ijmedinf.2007.08.011.