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"Trust in Artificial Intelligence: An Empirical Investigation of Acceptance Across Multiple Contexts."

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Abstract

The rapid development of Artificial Intelligence (AI) has led to a change in numerous areas of the world of work, including human resources management (HRM). This master's thesis examines how employees' trust in AI systems influences their acceptance of such technologies in HRM processes, with a particular focus on the areas of recruitment, selection, and training & development.

The Technology Acceptance Model (TAM) serves as the theoretical basis, which is extended by the variable trust. To empirically test the hypotheses, a quantitative online survey is conducted among employees from various sectors. The study analyses the influence of trust, perceived ease of use, and various demographic variables on the acceptance of AI in HRM processes.

The data is analysed using descriptive statistics and multivariate methods, in particular regression analyses. The results show that trust plays a central role in the acceptance of AI technologies in HRM, particularly in situations where employees have little transparency or control over automatically generated, data- driven decisions. The work thus contributes to the further development of the Technology Acceptance Model and provides practical implications for the trust-promoting introduction and use of AI systems in human resource management.

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1. Introduction

Artificial intelligence (AI) has developed rapidly in recent years. The current era, aptly referred to as the ‘AI explosion’ (late 1990s to present), is characterised by a combination of factors that have revolutionised the field (Mnih et al., 2015; LeCun et al., 2015). AI is a multidimensional concept that refers to systems and technologies that are capable of learning, exhibiting human-like behaviour or mimicking states, solving complex problems and simulating a certain level of consciousness (Caluori, 2022; Gil de Zúñiga et al., 2024). In practice, this means that AI can perform tasks that previously required human intelligence, such as analysing complex data, recognising patterns and making decisions (Osborne & Frey, 2023).

The rapid development and spread of AI are having a significant impact on various aspects of working life, particularly in Human Resource Management (HRM) (Zehrer et al., 2022). AI systems offer a wide range of opportunities in the HR department, from automating time-consuming tasks in recruiting (Jain et al., 2022; Kaur, 2023) to improving employee retention through personalised onboarding programmes (Jain et al., 2022). For example, AI-based chatbots can be used in recruiting to answer applicant enquiries in real time and speed up the application process (Zehrer et al., 2022). AI-supported systems can also be used to analyse application documents in order to identify the most suitable candidates for a vacancy (Kaur, 2023). The use of AI brings many benefits, but AI-driven decision-making also raises concerns about transparency, fairness, and bias, which can undermine trust in these systems (Jarrahi et al., 2023).

Although AI holds enormous potential in HRM, trust in this technology remains a key challenge (O'Dell & Davenport, 2019). Trust is fundamental to the successful integration and use of AI systems, as it influences acceptance and use by HR managers and employees (O'Dell & Davenport, 2019; Jarrahi et al., 2023). Lack of trust in AI-based systems can lead to resistance, rejection and even damage to the employer brand (Jarrahi et al., 2023). For instance, if applicants feel that AI-supported selection processes are unfair or discriminatory, they may turn away from the company (O'Dell & Davenport, 2019). Furthermore, explainability and perceived control over AI- driven decisions play a crucial role in whether users trust and adopt these technologies (Rahwan et al., 2019).

Especially in specific application areas such as recruiting, selection, training and development, research into trust in AI is still in its early stages. While individual studies focus on the efficiency gains of AI in these areas (Zehrer et al., 2022; Jain et al., 2022), there is limited understanding of how trust in AI develops and manifests in these specific contexts. This research gap is significant as AI applications are increasingly used in HRM and trust in these systems is critical to their success and ethical implementation (Jarrahi et al., 2023). Addressing this gap is crucial for ensuring responsible AI adoption and mitigating potential risks associated with its use (O´Neil, 2016).

To contribute to this discussion, this thesis examines how employees' trust in AI influences their acceptance of these technologies in HR practice. A particular focus is placed on the application areas of *recruitment, selection*, *training & development*.

This master's thesis examines trust in HRM processes to provide a differentiated understanding of trust mechanism in the areas of *recruitment, selection* and *training & development*. The aim is to identify key influencing factors and their implications for both theory and practice. To achieve this, an online survey is conducted to analyse perceptions of AI trustworthiness, acceptance and concerns among HR professionals and employees.

The thesis begins with a literature review, outlining the role of AI in HRM, the concept of trust and the current state of research. The theoretical foundation is the Technology Acceptance Model (TAM) (Davis, 1989) as it provides a structured framework for analysing how perceived usefulness and perceived ease of use influence technology acceptance. TAM has been extended in numerous studies, for example through the inclusion of trust, particularly in areas such as e-commerce and information systems (Gefen et al., 2003, Wu et al., 2011. Its role in the acceptance of AI- based HRM systems remains underexplored. This thesis addresses the gap by building on the established TAM framework, integrating trust as an additional variable, and analysing its significance for the acceptance of AI applications in recruitment, selection, and training & development.

Hypotheses were then developed based on this theoretical model and the research question. The constructs of the hypotheses were operationalised with the help of an online survey, which enabled an empirical analysis of trust, acceptance and influencing factors. In the next step, the research methodology is explained in more detail, followed by an analysis of the results. Finally, it is analysed whether the hypotheses are supported or refuted, and implications for theory and practice are derived.

2. Literature Review

2.1 Introduction to Artificial Intelligence (AI)

Artificial intelligence (AI) is a multidimensional concept which refers to systems and technologies that can learn, exhibit human-like behaviour or mimic states, solve complex problems and simulate a certain level of consciousness (Calouri, 2022). The construct describes the concrete ability of artificial systems or non-human machines to perform tasks, exchange information, interact with their environment and exhibit logical behaviour.mar Thus, AI can be operationalised theoretically based on two dimensions, namely the level of performance and the degree of autonomy. The level of performance comprises the AI's ability to perform tasks, make decisions and predictions. The degree of autonomy describes the extent of human input, interaction and supervision that influences the AI's actions (Gil de Zúñiga et al., 2024). AI, which has its roots in philosophy, mathematics, computation, psychology and neuroscience is becoming the "new normal" in both the manufacturing and service sectors (Kumar & Tahkur, 2012). However, the definition of AI is subject to constant discourse and is characterized by the diversity of perspectives and interpretations of its components (Calouri, 2022).

Since its beginnings, AI has undergone considerable development. This development can be divided into three different eras, starting with the initial phase, followed by the industrialization phase and finally the explosion phase (Lu, 2019). In the early years (1956-1980), the term "AI" was introduced at the Dartmouth Conference and pioneering researchers focused on basic tasks such as solving mathematical problems and understanding simple language. The following "knowledge boom" (1980-2000) showed increased government funding, especially in Japan, with the aim intending to develop machines capable of human-machine communication, translation and image recognition, and generally focusing on "knowledge processing" (Lu, 2019). The current era of "AI explosion" (beginning in the late 1990s) is characterized by a combination of factors, such as the development of big data and graphics processors and the speech and image recognition they enable, which have revolutionised the field (Lu, 2019). Building on these foundations, the current wave of AI is largely powered by generative models and large language models like GPT-3, DALLE-2 and ChatGPT, which rely on massive datasets and millions to trillions of parameters, making a major departure from past AI paradigms and opening new avenues for research and application in different fields (Sengar et al., 2024).

Considerable efforts have been made in AI research to strengthen the theoretical foundations of the field. This includes the development of robust machine learning (ML) tools that could effectively process and analyse large amounts of data. The subsequent explosion of internet data combined with advances in computing power has led to significant breakthroughs (Mnih et al., 2015). A pivotal moment was the emergence of deep learning (DL) around 2012, which led to significant advances in areas such as speech and image recognition. These applications are now integrated into our daily lives, for example in the understanding of sentences and documents, classification tasks and the learning of various video games (LeCun et al., 2015).

Machine learning (ML) is the underlying concept that makes artificial intelligence possible. It comprises various algorithms that enable computers to learn and improve without special programming. It also shows how human cognitive abilities can be achieved through algorithms (Hongyuan & Mingying, 2018).

Deep learning, a specialised branch of machine learning, falls under the broad heading of neural information processing systems (NIPS). This wide-ranging field encompasses computer systems inspired by the intricate structure and complex functions of the human brain. These systems utilize artificial neural networks (ANNs), interconnected and partially hidden layers of processing units that learn by iteratively processing information and are therefore able to extract complicated features from data (LeCun et al., 2015). At its core, deep learning is characterized by extracting features from complex information by using the task of the bottom layer as input for the next layer and training it on huge datasets. This layer-by-layer learning process allows DL to recognize subtle patterns and relationships that might elude simpler models (Lu, 2019). By overcoming the limitations of earlier algorithms, deep learning has revolutionized the processing of complex data formats, particularly in the realms of image recognition and natural language understanding. In addition, the availability of huge datasets and ever-increasing computing power provided an ideal environment for the success of Deep Learning (LeCun et al., 2015).

Compared to traditional shallow learning approaches, deep learning offers significant advantages. It has higher classification and prediction accuracy, uncovers complex non-linear relationships within the data and reduces the need for manual feature creation, which requires tedious manual extraction of features from data (Lu, 2019). Another recent development is the increasing use of robots, especially with the proliferation of smart home technologies and the *Internet of Things,* where robots can act as centralized control systems (Bogue, 2017).

In modern organisations, AI plays a crucial role in automating tasks that were previously considered impossible to automate, leading to efficiency gains and cost savings. The technology optimises work processes, increases productivity and enables faster decision-making by providing deeper insights into data. AI-driven collaboration promotes new ways of interacting with customers and partners, for example through automated customer service or generative AI (Liu et al., 2018).

Generative AI, a sub-area of AI, refers to a class of AI models that can generate new content such as conversations, stories, images, videos and music. This new content is based on the patterns and structures used to train the AI (Frey & Osborne, 2023). In contrast, traditional or non-generative AI focuses on analysing existing data to make predictions, recognize patterns, or support decision-making (Dataforest, 2024). This capability of generative AI supports business innovation by expanding product lines, transforming existing content and developing new business models. In addition, generative AI increases competitiveness by fostering innovation and improving operational efficiency (Frey & Osborne, 2023).

Recent advances, such as generative AI, in the field of artificial intelligence are changing organisational structures and challenging traditional management theories. The impact of its use on the workforce, working methods and organisational structures can be significant. For this reason, critical reflection on the impact of this technology on society and the need for responsible and ethical implementation is also important (Budhwar et al., 2023). These changes in the use of AI raise important questions about the ethical and societal implications of AI and its impact on workforce dynamics and decision-making structures. As data and algorithms increasingly drive business decisions, traditional hierarchies may be redefined, requiring management theories to adapt to evolving technological capabilities (Baumann & Wu, 2023).

In order to provide a clear and concise overview the key concepts, technologies, and applications relevant to AI, Table 1, summarizes the most important terms used in this study. It includes foundational AI concepts, as well as enabling technologies, capabilities and applications. The table summarizes key AI terms and technologies in one place, providing readers with a clear reference point. It is necessary because it ensures consistency, contextualizes the discussion of AI developments.

Term	Explanation	Source
Machine Learning (ML)	Algorithms that enable computers to learn and improve without explicit programming.	Hongyuan & Mingying, 2018
Deep Learning (DL)	A specialized branch of ML using artificial neural networks to extract complex features from data.	LeCun et al., 2015; Lu, 2019
Neural Networks	Computing systems inspired by the structure and functions of the human brain.	LeCun et al., 2015
Big Data	Extremely large datasets that enable AI systems to process and analyse complex information.	Lu, 2019
Graphic Processors (GPUs)	Specialized hardware that supports AI developments like deep learning by increasing computer power.	LeCun et al., 2015
Internet of Things (IoT)	Network of interconnected devices that collect and exchange data.	Bogue, 2017
Speech Recognition	AI´s ability to understand and interpret human speech.	LeCun et al., 2015
Image Recognition	AI´s capability to identify and classify objects in images.	LeCun et al., 2015
Natural Language Processing (NLP)	AI´s ability to understand, interpret, and generate human language.	LeCun et al., 2015
Level of Performance	The extent to which AI systems can autonomously execute tasks, make data-driven decisions, and generate predictions, varying by task complexity and degree of human supervision.	Gil de Zúñiga et al., 2024
Degree of Autonomy	The extent to which AI systems require human input or supervision for their actions.	Gil de Zúñiga et al., 2024

Term	Explanation	Source
Task Automation	The application of AI and related technologies to perform repetitive or complex tasks that were previously done manually, improving efficiency and productivity.	Frey & Osborne, 2023
AI – based decision-making support	AI provides insights and recommendations to enhance decision- making processes in organisations.	Liu et al., 2018
Generative AI	AI systems capable of creating new content such as text, images, videos, or music using deep learning models.	Frey & Osborne, 2023; Liu et al., 2018
Smart Technologies	AI- powered devices that automate and control home environments through IoT integration.	Bogue, 2017

Table 1 Key AI concepts and technologies relevant for organizational processes

2.2 Impact of AI on the Labour Market

A job comprises various interrelated tasks, each contributing to the overall function of the workplace. When it comes to the question of the extent to which artificial intelligence will influence the future development of jobs, the basis of the forecasts should first be defined. Either the workplace itself or individual tasks that make up the workplace can serve as the basis for assessment (Brynjolfsson & Mitchell, 2017).

In their model, Frey and Osborne (2017) analyse multiple professions to determine their potential for automation. For this purpose, the US Department of Labor has developed an occupational information network that contains the so-called O* Net variables and corresponds to the three “computerisation bottlenecks”. With the help of these O* Net variables, the skills and abilities in these occupations are tested and assessed as to whether they contain the corresponding tasks. Regarding the O* Net variables, jobs are more likely to be automatable if there is a low level of perception and manipulation, creativity and social intelligence (Frey & Osborne, 2017). Felten et al. (2021), on the other hand, have developed a method to classify jobs and industries according to the extent to which they are potentially affected by advanced

AI technologies. For this purpose, ten AI applications were identified, including speech and image recognition and generation, functions for which artificial intelligence can be used and which are likely to have an impact on the world of work. The relationship of these AI applications to the 52 pre-defined O*NET skills was then analysed, particularly in terms of their usability for specific tasks. These skills served as the basis for determining the relative exposure of different jobs to AI. The study assessed individual job skill based on their frequency and importance, finding certain skills are more critical in some occupations than others. This highlights which roles are susceptible to AI impact, providing a basis for understanding potential workforce changes (Felten et al., 2021).

The discussion about the impact of technology on the workforce is often accompanied by the question of whether it should be automated or augmented (Tschang & Almirall, 2021). While the term automation is usually associated with the idea of human labour being replaced by technology, the term augmentation refers to a process in which humans and machines perform tasks together (Raisch & Krakowski, 2021). In academic literature, these two perspectives are often presented as opposing (Tschang & Almirall, 2021).

In the past, it was generally assumed that most activities would be automated (Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). Today, however, there is a greater tendency towards augmentation (Benbya et al., 2020; Davenport et al., 2020; Jarrahi et al., 2023). The goal should be to connect people with the right knowledge resources or people at the right time to make better decisions (O'Dell & Davenport, 2019). The increasing AI capabilities and the promising functions to achieve the goals may require different forms of division of labour between workers and intelligent machines than in the past. These roles will require new skills and competences for humans and a new mindset for intelligent machines. Workers need to develop perceptions, skills and work practices to take advantage of AI partners while avoiding automation pitfalls such as cognitive complacency or algorithmic aversion. Cognitive complacency refers to excessive trust in automated systems, which reduces one's own critical thinking, while algorithmic aversion describes the tendency to distrust or reject decisions made by algorithms, even when they are correct. These preparations should be carried out by organisations to put the capabilities of AI into practice that can only be harnessed and realised through an effective symbiotic partnership between humans and AI (Jarrahi et al., 2023). Another perspective, as advocated by Krakowski and Raisch (2021), argues that overemphasizing one option or the other can lead to negative organisational outcomes. Rather than separating the two approaches, they should be seen as complementary (Raisch &

Krakowski, 2021), resulting in a collaboration between AI and humans where the strengths of both parties are enhanced (Jarrahi et al., 2023).

Although Frey and Osborne (2017) assume that an entire job can only be considered automatable if all tasks are automatable, their argument is not generally accepted (Benbya et al., 2021). Instead, the prevailing view is that automating individual tasks, rather than work as a whole, is the usual approach (Benbya et al., 2021; Brynjolfsson & Mitchell, 2017; Parker & Grote, 2022). This is consistent with the methods used by Webb (2019) and Felton et al. (2021) to assess the impact of AI on work, which use task-based assessment and consider the automation of individual task areas within a job. It is important to note that the measurement of Felton et al. (2021) refers to the current nature of the occupation. Instead of relying on expert assessments or crowdsourced evaluations, this approach provides a snapshot of occupational exposure to AI based on the current nature of jobs, without predicting which tasks might be suited for AI or automation or how job compositions could change because of AI influence (Felten et al., 2021). New occupations with a different mix of skills and tasks are constantly emerging as the work landscape is constantly changing (Frank et al., 2019).

Since the 1970s, a "polarization" of the labour market can be observed, which is characterized by the fact that jobs in the "high-wage" and "low-wage" sectors have continued to increase, while jobs in the "medium-wage" sector have continued to decline (Goos & Manning, 2007). This trend can be explained by the theory of Autor et al. (2003). According to this theory, tasks can be divided into routine and non-routine tasks and manual and cognitive tasks, and it is predicted that routine tasks, which are both cognitive and manual, are more susceptible to technological replacement than non-routine tasks (Autor et al, 2003). Since high-wage jobs are characterized by non-routine cognitive skills and low-wage jobs are characterized by non-routine manual skills and are therefore replaced slower by computerization. This is considered to be the reason for job polarization (Goss & Manning, 2007). However, it was predicted that this polarization in the labour market would not increase further (Frey & Osborne, 2017). Nowadays, the assumptions of Autor et al. (2003) can be revised. As a result of technological advances, non-routine tasks can now be computerized alongside routine tasks and are therefore also susceptible to substitution.

According to Frey and Osborne (2017), the extent to which individual occupations can be computerized depends on whether the job involves tasks requiring sensory perception and physical manipulation of objects, as well as creativity and social intelligence. They categorize occupations as low, medium and high risk, with low-risk occupations being those that have a high proportion of tasks from the perception and manipulation, creativity and social intelligence categories, which primarily include white-collar occupations such as finance, management, teaching and media occupations. These assumptions go hand in hand with the fact that both wages and education levels are negatively correlated with the risk of computerization. This means that low-wage, low-skill jobs could be most at risk of being replaced by technological innovation, while high-skill, high-wage jobs are very unlikely to be replaced in the near future (Frey & Osborne, 2017). The key difference between Autor et al. (2003) and Frey and Osborne (2017) is that in 2003, it was assumed that routine tasks are more susceptible to automation, whereas by 2017, the opposite was argued—non-routine jobs are also increasingly at risk.

The prediction that highly skilled white-collar occupations with high levels of education will be particularly affected by current technological developments, including generative AI, can be confirmed by other studies (Felten et al., 2022; Webb, 2019; Zarifhonarvar, 2023). It can also be added that older workers in particular will be most affected by advanced AI technologies, likely due to lower digital literacy, less experience with AI tools, and potential difficulties in adapting to rapidly changing workflows (Man Tang et al., 2022; Webb, 2019).

However, the view of Frey and Osborne (2017) that occupations in manufacturing and construction are highly automatability e was refuted by Felton et al. (2021). While Frey and Osborne (2017) categorize occupations in the manufacturing and construction category as highly automatable, Felten et al., (2021) conclude that occupations in these fields that rely on manual skills and are considered “blue collar” industries are among the “lowest rated”ba industries in terms of the extent to which they may be affected by AI. Also, occupations that demand a high level of physical exertion, such as dancing, fitness training, and painting, are among the industries least impacted by advanced AI (Felton et al., 2021). On the other hand, according to Felton et al. (2021), professions in the financial sector and those that require a high level of education, so-called “white collar jobs”, i.e. precisely the professions that Frey and Osborne (2017) classified as relatively safe, are particularly affected.

These shifts in job vulnerability highlight the broad transformation that AI is driving across all industries, fundamentally changing not only employment patterns but also the global economy. The advent of AI has the potential to increase operational efficiency and innovation by (Ore & Sposato, 2021) and supported by (Chinnaraju, 2025; Davenport et al., 2020; Ngabalin, 2025). Machine learning and big data analyses are now indispensable tools for predicting market trends and making strategic decisions (Menzies et al., 2024).

As AI reshapes industries and economic structures, its impact extends beyond businesses themselves to fundamentally alter workplace environments and employee experience. The adoption of AI can impact an organisation's employees in multiple ways, inevitably influencing their well-being, as is the case with any technology-driven societal shift (Nazareno & Schiff, 2021). The COVID-19 pandemic underscored the critical role of technological change, profoundly shaping the workplace. First, it created an urgent need for remote work, compelling organisations to rapidly develop and implement technologies that support virtual collaboration (Carroll & Conboy, 2020). Second, it broadened the focus of digital transformation beyond customer-centric strategies to include the workplace itself, enhancing the employee experience and digitizing the relationship between businesses and their workforce (Iansiti & Richards, 2020). As a result, many businesses accelerated their technology adoption plans or expanded their use of emerging AI technologies in the workplace (Sundareswaran, 2021). The transformation of organisations extends beyond their future strategies—it is also reshaping workplace environments and employee experiences. The automation of tasks, workforce displacement, job elimination, skill redistribution, and the growing need for continuous upskilling present significant challenges to the modern labour market (Didem & Anke, 2021; Nazareno & Schiff, 2021). The integration of AI into professional settings brings both opportunities and risks for employees and their career prospects (Mera & Srivastavab, 2023). On the positive side, AI can automate repetitive and stressful tasks, enhance workplace flexibility, and foster greater trust, autonomy, and collaboration among employees (Soulami et al., 2024). However, not all workers view these advancements favourably—many fears job displacement and the potential mental health repercussions, including increased stress and depression (Brougham & Haar, 2018). In response to this new technology, changes in workplace configuration and organisational and personnel adjustments have become necessary (Menzies et al., 2024).

2.3 Key Areas of AI Application in Companies

According to Davenport & Ronanki (2018) AI can play a key role in supporting three critical areas within companies. These areas of application are (1) the automation of business processes, (2) gaining insights through data analysis and (3) interacting with employees and customers. The area of process automation relates to digital and physical tasks, such as back-office administrative and financial activities. This includes tasks such as automatically updating customer records with address changes or new services, as well as reconciling billing errors across different systems by extracting information from various document types. Various algorithms are used to recognise patterns in huge amounts of data and interpret their meaning. For instance, data analysis can predict a customer's likely purchases and enable personalised digital advertising. Additionally, it can be used to analyse warranty data to identify potential safety or quality issues. Interactions with employees and customers with the help of chatbots, intelligent agents and machine learning are relevant for the third area of application. By leveraging intelligent agents, organisations can provide 24/7 customer support to address a wide range of issues or set up internal websites to answer employee inquiries on topics such as IT, benefits, and HRM policies (Davenport & Ronanki, 2018).

The business applications described above demonstrate how AI supports work processes. At the same time, the use of AI affects many aspects of working life. Most commonly deployed AI systems are designed for specific, single- domain tasks ("narrow AI"), such as image recognition, chatbots, recommendation engines, or predictive analytics. Despite their limited scope, these systems can outperform humans in certain tasks, such as pattern recognition, data classification, or anomaly detection (Bankins, 2021). While Davenport & Ronanki (2018) describe how AI supports companies through process automation, data- driven insights, and employee or customer interaction, narrow AI provides the technological foundation that enables these applications in practice.

Various examples illustrate the transformative potential of AI, including autonomous driving, conducting meaningful conversations through chatbots, selecting required products through recommendation systems, selecting promising applicants through software based on application documents and creating medical diagnoses from X-ray images and other data. The number of AI applications will continue to rise in the future because the underlying technology is becoming increasingly accessible (Voss, 2022). Improving the customer experience and tailoring content to individual preferences can also be achieved through AI systems (Huang & Rust, 2022). AI techniques contribute to more precise predictions in advertising and optimise the reach and effectiveness of marketing campaigns for various products and services (Menzies et al., 2024).

One area where AI´s impact is particularly significant is human resource management (HRM). AI technologies are transforming traditional HRM practices by addressing challenges in an increasingly globalized and competitive business environment. Palos-Sánchez et al. (2022) outline a conceptual structure that highlights key trends, particularly the role of big data and machine learning in HRM. AI-powered data analytics accelerate decision-making by processing vast datasets to generate actionable insights, improving efficiency in HRM processes (Caputo et al., 2019).

A key takeaway from the previous chapter is that AI technologies are revolutionizing HRM by transforming traditional practices and addressing a wide range of challenges in an increasingly globalized and competitive business environment.

2.4 AI in Human Resource Management

The term Human Resource Management is used to describe all organisational activities concerned with the recruitment and selection, job design, training & development, appraisal and reward, leadership, motivation and control of employees (Wilton, 2022). HRM encompasses the entirety of guidelines, strategies, processes and practices that shape and manage the relationship between employer and employee. Since the mid-1980s, human resource management has evolved from a largely administrative, operational function to an area of management that is considered important to the viability of organisations and to sustainable competitive advantage (Wilton, 2022).

In their paper, Tambe et al. (2019) describe an HRM life cycle and discuss the various HRM operations. The cycle begins with recruitment and deals with identifying potential candidates and convincing them to apply for the company. The next step is the selection of candidates to receive job offers. Onboarding is the next point in the life cycle and refers to the integration of an employee into the organisation. The training process aims to improve employee performance. Performance management is needed to identify good and bad performance. Promotion is also part of the operations and refers to who determines who is promoted and how well performance in new roles can be predicted. Employee retention is also one of the steps and deals with whether it is possible to predict who will leave and so manage the level of employee retention. The final point is employee benefits, where it is crucial to understand which benefits are most important to employees (Tambe et al., 2019). A central concern of HRM is to attract, motivate, and retain highly qualified employees from diverse backgrounds. This is crucial to ensuring the organization's competitiveness. Today, companies are focusing not only on addressing internal and external talent shortages but also on minimizing employee turnover. To support these goals, organizations are increasingly using technological solutions, for example, to optimize compensation and benefit programs (Dulebohn & Marler, 2005; Fay & Nardoni, 2009).

Employees remain crucial in today´s service and knowledge organisations, as companies increasingly compete based on their workforce´s skills, adaptability, and engagement (Huselid, 1995, O. C. Tanner, 2023; Roach, 2023). Consequently, talent acquisition is becoming increasingly important, as human capital – the collective knowledge, skills, and abilities of employees that contribute to organisational productivity (Becker, 1962) - is one of the most important factors in today's business world (van Esch & Black, 2019). One of the primary goals of human resource management is to attract, motivate and retain talented employees (Katz & Kahn, 1978). To achieve these goals, HRM systems must be designed to meet several key objectives (Stone et al., 2003). For example, selection systems should be used to recruit the best candidates and ensure that people and jobs fit the organisation's objectives. Furthermore, training & development opportunities must be offered as job requirements change (Johnson et al., 2021). These approaches complement the HRM life cycle steps described by Tambe et al. (2019), particularly in the areas of recruitment, selection, onboarding and training.

In the context of implementing HRM recruitment strategies, the recruitment process for university graduates is typically divided into two phases. In the first phase, companies review applicants' CVs to decide which candidates should be invited for an interview. In the second phase, the interview, companies assess the skills of the applicants in order to make a final hiring decision. The two phases are logically linked, as employers review applicants' CVs based on skills that are most important in the decision making (Humburg & van der Velden, 2015). By effectively managing each stage of the recruitment process, HR can ensure that they are not only attracting a diverse applicant pool, but also potentially selecting the right candidates.

As already explained, human capital plays an important role in recruitment decisions. Human capital refers to the accumulated knowledge and skills that directly contribute to the productivity of both individuals and organisations (Becker, 1962). Both cognitive and non-cognitive skills contribute to an individual's human capital stock and consequently to their productivity (Heckmann et al., 2006). Organizations are faced with the challenge that the human capital of applicants is not fully recognizable during the selection process (Humburg & van der Velden, 2015). The credibility of the information used for decision-making is important in terms of assertiveness (Jatoba et al., 2019).

The candidate experience is closely linked to these recruitment challenges. It begins with an exchange between the applicant and a potential employer in which both parties try to present themselves in a positive light to attract each other (Dineen et al., 2002). In most cases, applicants spend a lot of time and effort on the job search, and their application decisions are influenced by several factors. They are often concerned about the submission of applications, invitations to interviews and feedback on interviews (Derous et al., 2004). To ensure a positive experience in the application process, employers must conduct consistent and timely reviews of applications and provide prompt feedback to applicants (Doherty, 2010). Open communication with applicants throughout the application process facilitates this (Melanthiou et al., 2015). Failure to provide timely feedback can lead to a negative perception of the organisation, which can spread through word of mouth and make the company appear less attractive (Ore & Sposato, 2021). A positive application experience is closely linked to the employer brand and the positive image that a company conveys (Armstrong & Taylor, 2017).

The first step is to attract a diverse and motivated pool of candidates. Effective recruitment not only improves the skills and diversity of the workforce, but also helps increase customer satisfaction, promote innovation, and foster creativity (Cox, 1993). When companies attract many qualified applicants, they can select more effectively and hire the most suitable candidates for the respective positions (Johnson et al., 2021). A key challenge is to identify those who are particularly qualified from the large pool of applicants (Ideal, 2019). Over time, different technologies have been used to attract candidates—from passive, one-way methods such as online job postings and job portals to interactive formats such as virtual career fairs. According to a survey by StepStone, around 90% of large companies in seven countries use at least one of these technologies to advertise jobs and facilitate online applications (Mackelden, 2013).

Another goal of HRM is to select the most suitable candidates while ensuring that the diversity of applicants in the labour market is reflected (Guion, 1965). In recent years, technology has significantly influenced this process, as some organizations now use electronic screening tools to support the recruitment process (CedarCrestone, 2010).

A third important goal of HRM is to improve the knowledge, skills and abilities of employees with training & development. A variety of technologies have been used by organisations to more effectively design and manage the training process. These initiatives range from the online-only delivery of training materials to the use of a variety of technologies to deliver course content and support communication with trainees (Stone et al., 2015).

One of the most important objectives for the HR department is the effective management of employee performance. This includes assessing current performance, identifying high and low performers and providing feedback to employees. In 2014, 93 % of U.S. organisations surveyed were already using some kind of electronic performance management system. The survey collected responses from HR and IT management and business leaders with knowledge of the HRM technologies in use and planned (CedarCrestone, 2014). Technology is used in the performance management process primarily in two areas: to measure employee performance and to provide feedback on performance results (Cardy & Miller, 2005; Fletcher, 2001).

The use of technology has fundamentally changed the management of HRM processes, particularly about the collection, storage, use, and processing of information about applicants and employees. It has also transformed the work environment, labour relations, and supervision (Stone et al., 2015). Technological development changes the practice of human resources, as employees interact with and are influenced by Human Resources Information Systems (HRIS) throughout their employment journey - from recruitment to retirement. Such a system is "used to capture, store, process, analyse, retrieve and distribute information about an organisation's human resources" (Kavanagh & Johnson, 2018, p. 8). The way in which employees are recruited, selected, trained and remunerated has changed (Parry & Tyson, 2008).

The field of human resources is currently in the midst of a major revolution through the use of AI, which is being used in more and more functions in the field. The performance of sub-areas that were once performed entirely by humans is being transformed by AI (George & Thomas, 2019). A human resource department uses strategic approaches to ensure efficient management of personnel throughout the organisation. This system involves people, processes and technology to improve organisational performance (Potgieter & Mokomane, 2020). AI helps organizations make HRM functions more efficient and effective by making management processes more flexible and precise (Nankervis et al., 2021). Furthermore, AI should enable HRM to understand and control a data collection process so that this process is integrated into an organisational and economic efficiency strategy (Varma et al., 2022). There are various areas in HRM where AI can be used. These include 1) talent search and recruitment, 2) training & development, 3) performance analysis, 4) career development, 5) compensation and 6) staff turnover (Qamar et al., 2021; Yahia et al., 2021). The integration of AI in HRM has not only revolutionized traditional processes but also introduced sophisticated tools and techniques, which are transforming the way HR departments operate and make decisions.

In their study, Qamar et al. (2021) showed that AI is used in HRM in various areas with the help of different techniques. These include (1) expert system, (2) fussy logic, (3) artificial neural network, (4) data mining, (5) genetic algorithm and (6) machine learning.

Expert systems are programs that transform the knowledge of domain experts into logical structures to solve unstructured problems and support the development of comprehensive information systems. They facilitate the decision-making process by giving decision-makers quick access to valuable knowledge that would otherwise be difficult to access (Lawler & Elliot, 1996). Such systems assist HRM in addressing unstructured problems and play a key role in the development of comprehensive human resource information systems (Byun & Suh, 1994). This technology is primarily used in personnel planning, remuneration, recruitment and personnel management (Malik et al., 2022).

Fuzzy logic is another technique that is used in various research areas (Salmerón & Palos-Sánchez, 2019). The logic makes it possible to deal better with ambiguities and uncertainties and to make decision-making more flexible. Fuzzy logic is a method used to deal with fuzzy, imprecise, or unclear information. The logic helps to make decisions when there are no clear-cut answers by considering the various possible manifestations of a problem (Selden et al., 2000). In the case of HRM, this logic is based on different levels of membership, which indicate the degree to which an element belongs to a set and can vary between 0 and 1. A value of 0 means the element does not belong to the set at all, while a value of 1 indicates full membership. Fuzzy logic makes it possible to quantify uncertainties in the data and make predictions for future scenarios, thereby supporting decision-making processes (Kimseng et al., 2020). For example, this logic is used in personnel selection and optimal workforce design (Qamar et al., 2021). Applicants can be assessed based on criteria such as experience, education and skills, without each criterion requiring a clear 'yes' or 'no' answer. Instead, the applicant is rated on a scale that also allows for nuances such as 'somewhat suitable' or 'very suitable' (Mavi & Mavi, 2014).

Artificial neural networks are also among these techniques, and this application is a simplified model developed to mimic functions of the human brain and learn from examples by adjusting the weights of the connections between the elements (Huang et al., 2006). It is one of the most important predictive practices and is mainly used in personnel selection, recruitment and performance management of employees by analysing past data and optimizing decisions automatically (Qamar et al., 2021).

Data mining is the extraction of valuable but hidden information. This allows organisations to turn important and useful information and patterns into competitive advantages (Huang et al., 2006). This technique is mainly used for recruitment, performance evaluation and talent management (Qamar et al., 2021).

The genetic algorithm is also one of these techniques. It is a search method inspired by natural evolution, where population of potential solutions is iteratively modified through processes (Masum et al., 2018). These concepts from the nature such as replication (the passing on of good solutions), mutation (the random alteration of solutions to discover new options) and crossover (the mixing of solutions to find better ones) are used to search for the best solution to the problem (Fowler et al., 2008). In the HR department a genetic algorithm can be used to create the best possible personnel planning, to transfer employees to the right positions, or to assess which candidates are best suited (Wi et al., 2009). This algorithm is also able to solve mathematical problems (Zhang et al., 2021).

Machine learning is also one of the techniques used. As defined earlier, it comprises various algorithms that enable a machine to learn and improve without explicit programming (Hongyuan & Mingying, 2018). It is mainly used in decision-making for HR managers and in sales forecasting (Hamilton & Davison, 2022).

Building on the role of AI in HRM, the following section focuses specifically on its application in recruitment and selection.

2.4.1 AI in the Recruitment and Selection Process

Foundational Concepts and Applications

The recruitment process is a crucial part of HRM and serves as a gateway to building a talented and diverse workforce. Traditionally, this includes a thorough job analysis to determine the specific requirements and specifications for different roles. Organisations use a variety of techniques to conduct job analyses, such as questionnaires and interviews, yet the process can be very time-consuming. The use of online job analyses, which means systematic job analyses conducted via digital surveys and platforms to collect information from subject matter experts about job requirements and specifications, can greatly simplify and streamline this process (Gatewood et al., 2016).

As organisations navigate this recruitment landscape, they must recognize that in the age of globalization, work tasks are becoming increasingly specialized. While automation is changing the nature of many white- collar jobs, highly qualified and specialized profiles mean high demand and therefore represent a scare resource in the competition of talent (Ore & Sposato, 2021). A key competitive advantage for organizations lies in human capital, as it is an intangible resource that is difficult for competitors to imitate (Kearney & Meynhardt, 2016).

Companies are increasingly realizing that careful selection and recruitment of employees is crucial to avoiding costly bad hires and ensuring long-term business success (Ore & Sposato, 2021). One mistake is not to hire the right people in terms of performance and passion, because if employees do not fulfil their tasks, it puts a strain on the team and makes work more difficult for everyone. Furthermore, negative feedback from references should be considered, and close attention should be paid to how the candidates present themselves. It can also be a problem that recruiters fill out the entire interview themselves and do not even let the applicant contribute (Welch & Welch, 2013).

To address these challenges and streamline the recruitment process, organisations are increasingly turning to AI.

The study by Albert (2019) highlights various AI applications – such as chatbots, screening software, and task automation tools - and identifies eleven areas in the entire recruitment and selection process in which AI applications can be used. Various AI applications are applied in recruitment, such as chatbots that mimic human conversation and provide instant answers to questions. Other examples include the use of a screening software to sift through a large number of CVs or automated tools that are responsible for scheduling appointments. However, HR professionals rely mainly on chatbots, screening software and task automation tools (Albert, 2019). More recent studies show that AI is now widely integrated into HR work. HR professional use AI for candidate recommendations and globally, 72% of HR leaders report using AI tools weekly, such as ChatGPT and chatbots (LeFebvre, 2024; Tilo, 2025).

Technological Evolution of Recruitment

The methods used in recruitment have evolved considerably in recent years. According to Adelmann & Wiedmer (2020) the technological changes can be illustrated using four development stages, Recruitment 1.0 to 4.0.
Recruitment 1.0 began in 1995 with the use of the internet for hiring. This was followed by Recruitment 2.0 in 2005, characterised by the rise of Web 2.0, which emphasized interaction and social media. In Recruitment 3.0, starting in 2007, social networks transformed into professional platforms increasingly, leading to the rise of social recruiting. Finally, Recruitment 4.0, which emerged in 2016, introduced data-driven hiring and the use of robots and automation

in recruitment processes (Adelmann & Wiedmer, 2020). In recent years, recruitment technology has evolved even further. Today, organizations use AI to make data-driven hiring decisions (Qin et al., 2023), and AI tools such as screening software and chatbots are routinely used to improve efficiency and objectivity in recruiting (Cavescu & Popescu, 2025). Furthermore, AI tools can now be used for the entire employee life cycle (Barghi et al., 2022).

AI can already be used in the beginning of the recruitment process, for example to forecast future events such as vacancies and the resulting personnel requirements. The use of AI will also make it easier to advertise jobs. Conclusions can be drawn from existing data regarding ad classification, promising keywords and the selection of suitable platforms for job advertisements (Adelmann & Wiedmer, 2020).

Job posting on the relevant websites and finding the right candidates are rather tedious and time-consuming tasks. Websites, such as LinkedIn, use machine learning algorithms that make job recommendations to applicants based on their CVs, keywords used by applicants, their search history and their list of connections (George & Thomas, 2019).

Companies are increasingly using chatbots aiming to provide candidates with information on vacancies at an early stage (Adelmann & Wiedmer, 2020). In many cases, there is a time gap between accepting the offer for the new job, resigning from the old company and starting the new job. During this period, applicants may reconsider their decisions. To keep new employees on board, it is very important to send follow-ups at regular intervals. In many cases, this process is carried out with the help of AI (George & Thomas, 2019). Digital recruitment is defined as the use of information and communication technologies to maintain potential candidates' interest in the organisation throughout the application process and to influence their decisions regarding applications (Johnson et al., 2021). Nowadays, large parts of society spend a vast amount of time in the digital world, making it crucial for companies to search for new talent through the digital environment (Black & van Esch, 2021).

This increased use of AI also impacts employer branding. The study by Baratelli and Colleoni (2022) examined the extent to which the use of AI in the recruitment process can increase the attractiveness of an employer from the perspective of applicants. For this purpose, a random sample with equal gender distribution was surveyed. A structural equation model was used to compare the results. The results showed a positive relationship between employer branding and AI and revealed that AI-supported tools are perceived positively by potential applicants, in particular. The results of the study show that the use of AI has a positive impact on employer branding and thus supports talent acquisition (Baratelli & Colleoni, 2022).

AI- Powered Selection

AI can be used in many ways in the candidate selection process. Various methods, such as deep learning and text mining, are increasingly being used to process data and analyse application documents. With the help of algorithms, CVs are searched for keywords relevant to the position and simultaneously verified using social and professional networks. During the recruitment process, data is generated from each employee, and this is then extracted, converted and summarized during the data generation phase. At this point, machine learning comes into play and algorithms are developed that contribute to a permanent improvement in task fulfilment (Adelmann & Wiedmer, 2020).

Building upon this automated data analysis, the increasing automation in various aspects of selection includes not only the screening of applicants, but also the evaluation of video applications through verbal and non-verbal body language analysis (Jia et al., 2018).

To further enhance the efficiency and effectiveness of the selection process, some companies, such as IKEA, use AI technologies for initial selection interviews. Coordinating appointments with pre-selected applicants can also be facilitated and accelerated using AI technologies. Interviews conducted by AI systems are also relevant for qualification interviews and not just for initial selection. Voice, language, key words as well as intonation, facial expressions and body language can be analysed during standardized interviews using intelligent, computer-aided systems and compared with characteristics of high-performing employees that serve as benchmarks. Although AI can already make predictions about candidates' accuracy of fit and career success, the final selection is still made by a recruiter. Contract negotiations and the start of work, which characterize the third and final phase of the recruitment process, are currently carried out without any significant use of AI (Adelmann & Wiedmer, 2020).

Benefits of AI in Talent Acquisition

AI offers a multitude of benefits that are revolutionizing the talent acquisition landscape. These advantages can be broadly categorized as follows: (1) resource savings (time and cost), (2) process improvement (automation and efficiency) and enhanced decision- making (accuracy and objectivity), (3) reduction of bias and (4) empowerment of HR professionals.

AI enables significant resource savings in the recruitment process, reducing time-to-hire and lowering personnel costs. This is achieved through automating time-consuming tasks such as resume screening, initial candidate communication, and interview scheduling (Adelmann & Wiedmer, 2020). Companies utilizing AI can save up to 71% of the cost per hire for recruitment processes and related activities. Therefore, the effectiveness of recruiters is three times higher (Min, 2017). However, these figures are based on practitioner reports, and the exact criteria for efficiency were not specified.

AI drives both process improvement and enhanced decision-making. By automating monotonous selection tasks, AI allows HR managers to manage higher volume of applicants with greater efficiency (Ore & Sposato, 2021). This automation leads to a substantial reduction in workload. For instance, Wislow (2017) states that talent acquisition software reduces 75% of the workload of the recruitment process. Furthermore, AI enhances accuracy and objectivity in the recruitment process. Machine learning can minimize errors and the provision of more and better prepared information leads to improved decisions (Michailidis, 2018). Due to increased accuracy and objectivity, there is an opportunity for improved decision-making, which can lead to an increase in quality (Adelmann & Wiedmer, 2020).

AI has the potential to reduce bias in hiring decisions, by eliminating information such as gender, age or origin. This effect strongly depends on the quality and neutrality of the data used for training the algorithms. If the data itself contains historical biases, AI may even reproduce or amplify them (Adlemann & Wiedmer, 2020).

AI empowers HR professionals by reducing administrative work, which allows them to focus on planning and organising HRM tasks (George & Thomas, 2019), while employees can focus on tasks that create added value (Pillai & Sivathanu, 2020). To ensure smoother processes and increased efficiency, it is important to make them less time-consuming while creating greater value for the HR department (George & Thomas, 2019).

Human Augmentation: Balancing AI with HRM Expertise

While AI offers increasing power to HRM, HR departments can focus on the strengths of AI in the workplace (George & Thomas, 2019). Ethical considerations, along with the increased flexibility for previously overlooked activities such as communication, interaction, and creativity, indicate that AI will complement rather than replace HRM staff. Additionally, many companies still prefer to make final hiring decisions themselves due to ethical considerations (Adelmann & Wiedmer, 2020).

The impact of AI on recruitment is particularly significant especially from the candidate´s perspective. Research by van Esch et al. (2019), conducted with a general online survey sample rather than within a specific industry context, found that attitudes towards companies that use AI in the recruitment process significantly influence the likelihood of potential candidates completing the application process. The novelty factor of using AI in the recruitment process acts as a mediator and has a further positive influence on the likelihood of applying. These findings indicate that, despite potential concerns, applicants' fears do not appear to significantly reduce application completion. On the contrary, the study suggests that the use of AI in recruitment can be encouraged, especially by targeting potential candidates who already have a positive attitude towards both the company and AI (van Esch et al., 2019). While these insights emphasize the perspective of the applicants, it is equally important to consider the implications for organizations themselves. Beyond recruitment, AI presents both opportunities and challenges for workforce employability. On the one hand, the development and operation of AI require specific technical expertise, which indicates an increase in technical jobs. On the other hand, it is precisely this challenge for the qualification and employability of middle management, older employees and all human resources of the company (Khatri et al., 2019).

An additional reason against full automation is the need for human characteristics such as empathy and emotions, which are still required for cultural fit assessment and other activities such as relationship building and negotiation (Ore & Sposato, 2021). The results of the study by Bhardwaj et al. (2020) make it clear that there is a positive relationship between the increased use of AI at work and better functional performance of the HR department. Since AI is significantly associated with both innovativeness and usability, it positively influences HRM work. It is also observed that AI performs better than humans by lowering attrition rates and increasing talent retention.

While AI´s role in recruitment is significant, it also extends beyond this initial phase into various other important areas of HRM. Most of the research by Palos-Sánchez et al. (2022) relates to its use in the recruitment and selection of new employees, but there are several other important areas of application, such as training, development and staff rotation. The interest in talented and well-trained staff is increasing, as this is necessary to survive in the changing environment and strong competition. It is important to note that talent not only needs to be found but also needs to be trained to provide a long-term competitive advantage.

2.4.2 AI in Training & Development

Training & development (T&D) is a key strategic tool for attracting unique human capital and enhancing overall organisational performance (Botke et al., 2018; Chung et al., 2021). It refers to ‘a set of systematic and planned activities designed by an organisation to provide its members with the opportunity to learn the skills necessary to meet current and future job requirements’ (Werner & DeSimone, 2006, p. 5). T&D plays a crucial role in improving employee performance, fostering career development, and enhancing organisational competitiveness (Niati et al., 2021). It encompasses not only ongoing skill development and career growth but also the onboarding of new employees, which introduces them to company culture, policies and procedures (George & Thomas, 2019). Training is a method that is used to change the behaviour of employees through events and programmes, enabling them to perform their tasks more effectively. Investment in *training & development* programmes is an important factor in the implementation of customer-centric business tactics (Bashar et al., 2024).

As technological advancements reshape business landscapes, organisations must secure distinctive, company-specific human resources to remain competitive (Salas et al., 2012). As global competition intensifies, both operations and human resource management are evolving, requiring strong managerial support and an adaptable corporate environment. Factors such as the existing training culture, organisational climate and environmental dynamics are indispensable points here (Diamantidis & Chatzoglou, 2019). Organisation's investment in *training & development* is a complex and long-term process influenced by various internal and external business situations rather than by simple, short-term decisions for a single event (Botke et al., 2018; Xue et al., 2008).

To respond to these challenges, innovative technologies, especially AI, have gained significant attention in the evolution of T&D. AI is transforming *training & development* by optimizing onboarding, personalizing learning experiences, streamlining coordination, enhancing performance evaluation, and revolutionizing e- learning technologies. Its strategic implementation enables organisations to improve employee engagement, productivity, and adaptability in an evolving business landscape (Chowdhury et al., 2025).

A practical and one of the earliest applications of AI in T&D is in employee onboarding. Most organisations conduct training and orientation programs for all new employees to introduce them to the company culture, policies, rules and regulations (George & Thomas, 2019). In a study by Miller (2016), it was found that almost 90% of employees forget important information during the orientation period. To enable employees to ask questions about company policy, employee benefits and insurance at any time, many companies have introduced chatbots to perform these tasks (Min, 2017). This process allows employees to access necessary information on demand, improving retention and engagement in the onboarding phase (George & Thomas, 2019).

Beyond onboarding, organisations are increasingly leveraging AI- based learning platforms, such as learning management systems, chatbots, and interactive virtual environments, to enhance training effectiveness (Juang et al., 2007). A variety of technologies are used in organisations to design and manage the training process more effectively. These 'e-learning' initiatives range from the simple online delivery of training materials to the use of a wide range of technologies to deliver course content and support communication with trainees (Stone et al., 2015). According to the ASTD 2012 State of Industry Report, which surveyed 461 organizations across diverse range of industries and sizes in the United States, U.S. companies invested approximately $156.2 billion in employee learning in 2011. Notably, more than 25% of corporate training hours took place online, with nearly 40% of initiatives being technology enabled (Miller, 2012). Various AI systems, including interactive voice response or text-to-speech, can assist trainers in crating learning materials, while natural language processing aids in developing adaptive learning models and speech recognition- based tools (Chapelle & Chung, 2010).

Beyond content delivery, AI enhances training personalization and engagement by the customization of learning programs based on individual employee needs and work experience (Poquet & de Laat, 2021). AI-supported learning programs can be used to promote employee retention, which in turn can encourage innovative learning approaches among employees (Tripathi et al., 2012). The automation of training recommendations not only optimises learning efficiency but also ensures alignment with company policies and job requirements (George & Thomas, 2019). Additionally, AI facilitates remote learning through app- based solutions and virtual learning environments, providing flexibility and accessibility for employees (Juang et al., 2007). By personalized training, AI offers tangible benefits for both employees and organizations (George & Thomas, 2019). AI also significantly improves the efficiency of training coordination by automating scheduling, tracking employee progress, and managing course enrolments. AI can also handle feedback collection, which optimises administrative tasks and reduces the burden of HR managers (George & Thomas, 2019). As a result, organisations can allocate resources more effectively while maintaining high- quality training programs (Nankervis et al., 2021).

As training progresses, AI extends its influence to performance evaluation and feedback evaluation. AI plays a crucial role by developing measurable goals for each individual and tracking individual progress. This makes regular feedback systems simpler and generates actionable insights for employees and managers. AI can not only measure current levels of employee engagement, but also predict future engagement, turnover rates, performance levels, and other relevant metrics (George & Thomas, 2019). Many benefits can arise from these applications as evidence-based decision making occurs (Colson, 2019). Additionally, online surveys supported by AI allow organisations to systematically gather employee feedback on training programs, improving overall effectiveness (George & Thomas, 2019). Robots and AI systems are also capable of social collaboration to support humans in learning (Bankins & Formosa, 2020). AI can assist in all stages of training *& development* and, including assessing learning needs, designing instructional content, delivering and guiding learning, documenting progress, and evaluating outcoms (Sooraska, 2021).

Finally, AI provides numerous benefits in the area of *training & development*. Automation, using AI, enables processes to be carried out faster, more accurately and cheaper (Strohmeier & Piazza, 2015). A study by Concannon et al. (2005) found that AI motivates learners, influences other participants, facilitates learning plans and provides flexibility and ease. AI systems also allow courses to be offered to larger groups and make it easier to meet the needs of all age groups (Pandey, 2017). Artificial intelligence can recognize users' learning styles, and studies have shown that this can improve learning outcomes (Stone et al., 2015).

2.4.3 Challenges and Ethical Considerations of AI in Human Resource Management

While AI offers significant benefits in HRM, its implementation is not without challenges and ethical considerations. These concerns can be categorized into areas: (1) ethical concerns related to data privacy and security, (2) potential for algorithmic bias and discrimination, (3) challenges related to training data quality and availability and (4) the evolving role of HR professionals.

The use of AI in HRM raises ethical concerns regarding the handling of sensitive applicant and employee data (Bankins, 2021). AI- driven recruitment has the potential for legal, privacy, moral and defamation concerns for potential candidates, and companies need to find solutions to address these issues in their respective jurisdictions and be prepared to deal with any backlash or consequences from potential candidates (van Esch et al., 2019). Beyond privacy, another major concern relates to the risk of algorithmic bias in recruitment decision.

AI algorithms can perpetuate and amplify existing biases if not carefully designed and monitored. In automated AI-driven personnel selection, the algorithm learns to make the same decisions as those who work on generating training data in the HR department. This principle of learning highlights two of the most important sources of error in AI-based decisions. Firstly, the decisions made by an AI can only be as good as the training data. If the training data contains systematic errors, these errors will also be reflected in the future behaviour of the AI. This type of error has been observed in automatic personnel selection algorithms, for example. In this case, certain patterns of discrimination that were found in unfair decisions made by humans in a personnel department were learned by algorithms and thus perpetuated. The second problem that arises from the learning principle of AI concerns the handling of new or unusual data. AI can only derive general principles of action or decision-making beyond the learned area to a limited extent (Voss, 2022). Studies have shown that while AI can optimise recruitment and selection, companies should address ethical concerns to prevent biased hiring practices. If these considerations are not taken into account, companies could potentially be sued for discrimination in court (Ore & Sposato, 2021). Closely linked to bias are the challenges posed by the quality and availability of training data, which directly affect the accuracy and fairness of AI systems.

The effectiveness of AI in recruitment depends heavily on the availability of large amounts of high-quality training and unbiased training data. Since AI systems have no vested interest in neutrality and objectivity, unbiased training is a difficulty (Adelmann & Wiedmer, 2020). The reason for this is that AI tools, such as machine learning, make algorithm-generated hiring predictions based on the analysis of big data collected by different systems within the organisation (Ore & Sposato, 2021). The use of algorithms in personnel selection has already led to biased decisions regarding gender and origin (Dastin, 2018). Additionally, HRM functions vary widely across organisations, making it difficult to develop universally applicable AI models (Gélinas et al., 2022). This can lead to various types of problems caused by the lack of a sufficient database. Older applicants with a lower affinity for technology and people from lower socio-economic backgrounds can also be affected by discrimination through AI. Despite the many difficulties, non-discriminatory training of the systems is the biggest challenge to fully benefit from the opportunities of AI-assisted recruitment (Adlemann & Wiedmer, 2020). These technical challenges also influence the daily work of HR professionals, whose roles are evolving under the pressure of AI- driven tools.

AI also impacts HR professionals' roles, requiring them to adapt to evolving technology. The ease of applying for jobs online can lead to a flood of unqualified applicants, increasing the workload for HR professionals. A disadvantage may arise from the fact that e-recruiting, which refers to recruitment via online channels, could encourage applicants to apply for jobs without checking their suitability for the position, increasing the number of unqualified applicants. This can increase workload and waste valuable time as recruitment teams have to review numerous unsuitable applications (Ore & Sposato, 2021). Additionally, AI adoption has sparked concerns about job security, with employees fearing displacement by automation (Kong et al., 2021). AI-driven communication tools, such as chatbots, risk dehumanizing workplace interactions, underscoring the need for a balanced integration of technology and human engagement (Fritts & Cabrera, 2021). In training contexts, AI-based solutions can unintentionally reduce collaboration and social interaction among trainees, potentially lowering engagement and satisfaction levels (Piccoli et al., 2001). Rapid technological advances also demand continuous training for HR professionals to effectively integrate AI tools into HRM practices (Malik et al., 2021).

Despite these challenges, AI holds great potential to enhance HRM by improving efficiency, predictive analysis, and decision-making (Sekhri & Cheema, 2019). However, organisations must invest in bias mitigation strategies, transparent AI governance, and continuous workforce training to fully realize the benefits. The rapid expansion of AI tools, including OpenAI´s ChatGPT, Microsoft´s Bing, and Google´s Bard, has intensified discussions on AI´s role in business and the workforce (Menzies et al., 2024). While larger, innovative firms embraced AI, widespread adoption remains slow due to concerns over cost, ethical implications, and regulatory uncertainty (Albert, 2019).

AI success in HRM depends on its responsible implementation. Companies should proactively address ethical concerns, ensure fair and transparent decision-making, and equip employees with the necessary skills to navigate an AI-driven workplace (DiClaudio, 2019).

2.5 Theoretical Framework – Technology Acceptance Model (TAM)

After discussing the potential applications and both opportunities and challenges of AI in human resource management, it is important to anchor these findings in a theoretical framework that can systematically explain the introduction of technologies. To this end, the Technology Acceptance Model (TAM) is presented, as it provides a robust basis for analysing the acceptance of AI systems by users in organizational contexts.

The Technology Acceptance Model originated from research on validated scales for measuring technology acceptance. The original TAM model is based on two variables, namely perceived usefulness and perceived ease of use. These two determinants are important for predicting user acceptance. In the context of this study, acceptance refers specifically to candidates and employee's willingness to engage with AI- based HRM systems. Research shows that users are more willing to adopt technologies that are perceived as beneficial. An application that is perceived by users as more user-friendly has a higher probability of being accepted, all other things being equal (Davis, 1989).

Over the years, the model has been extended to include various external factors, depending on the context in which it is used. The TAM is a theoretical model that explains technology usage behaviour and has been validated across different technologies and populations. It is considered one of the most effective theories for describing user acceptance of technologies (Venkatesh & Davis, 2000).

A significant development in TAM research was the inclusion of trust as a key construct influencing the acceptance of technologies. Trust has a significant influence on TAM constructs, and this finding is particularly relevant in the context of AI-based technologies, as user trust in these technologies is crucial (Wu et al., 2011). In this context, TAM has been expanded to include multidimensional measures of trust in AI in order to gain a more nuanced understanding of how users interact with these technologies (Choung et al., 2022). Figure 1 visualizes the extended TAM model for AI applications, in which the central constructs of perceived usefulness, perceived ease of use, and trust are represented. The figure shows how the factors affect user acceptance and how trust is integrated into the existing TAM relationships as an additional influencing factor in order to better explain user acceptance of AI technologies.

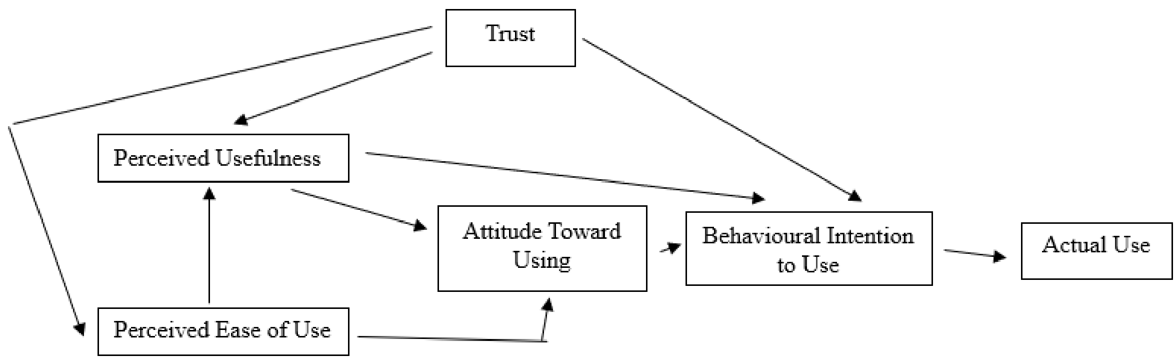

Figure 1 Research Design TAM Model

The extended TAM model provides a flexible framework that can be adapted to different AI systems. Specific trust constructs are incorporated into the original model, enabling a targeted investigation of trust in AI. This adaptability is a great advantage and for this reason the TAM model can be used perfectly for researching acceptance and trust in AI technologies (Choung et al., 2022). While the TAM provides a theoretical framework for understanding user acceptance of AI systems, it is equally important to look more closely at the practical applications of AI in different business contexts, as these can further influence user perception and trust.

The TAM model can be used in a variety of ways in different areas. An example of this is the use of an extended TAM model to investigate the acceptance of AI-based robo-advisors in the financial sector (Park et al., 2017) or of Internet of Things technologies in smart homes (Belanche et al., 2019).

There are various studies that use an extended form of the TAM model to investigate trust in various AI technologies. For example, the study by Fernandez-Carames and Fraga- Lamas (2023) examines the acceptance of AI in Internet of Things applications. These studies showcase how the TAM can be tailored to specific AI contexts while maintaining its core principles. Building on this perspective, Fernandez- Carames and Fraga- Lamas (2023) examine how the two main constructs of the Technology Acceptance Model — perceived usefulness and perceived ease of use — influence individuals' willingness to accept and adopt these technologies. The study examines various applications in sectors such as healthcare and smart cities. Additionally, it addresses challenges such as data protection and interoperability. The study concludes that while the integration of AI into the Internet of Things holds significant potential, successful implementation requires careful consideration of technical, ethical, and user acceptance factors as outlined in the extended TAM framework (Fernandez- Carames & Fraga- Lamas, 2023).

Recent research findings confirm the continuing relevance of TAM for the introduction of AI in various areas, including human resource management. Almeida et al. (2025) investigated the introduction of AI among recruiters and found that perceived usefulness and perceived ease of use remain key predictors of adoption decisions. Similarly, Hassan (2025) analysed the implementation of AI in talent acquisition and emphasized that these two constructs strongly influence user acceptance. Other studies show that TAM is also used in other sectors to investigate the acceptance of AI. Song et al. (2025) examined the introduction of AI in organizational decision-making processes and showed that extended TAM constructs can capture the impact of AI on performance outcomes. Furthermore, Ibrahim et al. (2025) validated an extended TAM framework by integrating personality traits and attitudes toward AI and demonstrated its flexibility for contemporary AI applications in organizational contexts.

The extended TAM model emphasizes trust as a key factor influencing the adoption of AI. To deepen the understanding of this construct, the following section examines trust and transparency in AI systems, highlighting the mechanisms, dimensions, and determinants that shape individuals' perceptions, trust, and interactions with AI technologies in an organizational context.

2.6 Trust and Transparency in AI Systems

Mayer et al. (1995) describe trust as a combination of belief in the competence, benevolence, and integrity of another party. Ability refers to other party´s skills or competences to perform a particular task successfully. Benevolence describes whether the intentions of the trusted party match those of the trust giver. Integrity describes the moral orientation and sense of justice of a trustworthy party. They act according to their own principles that are acceptable to the trusting party, demonstrating behavior that is honest and consistent with these principles (Mayer et al., 1995).

According to the literature, there are two main ways to strengthen trust, namely the cognitive and the affective way (Johnson & Grayson, 2005). The cognitive pathway, which is often the focus in research (Hancock et al., 2011), relies on knowledge, experience, and rational evaluation of an agent´s competence and reliability (Johnson & Grayson, 2005; Moorman et al., 1992). Humans are more likely to trust others who make fewer mistakes or demonstrate expertise (Jiang et al., 2004), whereas when interacting with machines, trust tends to drop sharply when errors occur due to higher expectations of perfection (Dzindolet et al., 2002). In contrast, the affective pathway is based on emotional and personality- related factors. One example is attachment style, which describes how individuals feel, think, and behave in relationships, typically assess as attachment security or insecurity (Ainsworth et al., 1978; Bowlby, 1982). Various studies have shown that attachment style is an effective predictor of different relationship outcomes (Gillath et al., 2016). From this, it can be deduced that attachment security is associated with more trust, while attachment insecurity is associated with less trust. This conclusion is also supported by various studies (Simmons et al., 2009). Affective trust is more subjective and less transparent to outsiders or processes such as risk assessment (Johnson & Grayson, 2005). Furthermore, this pathway is thought to be associated with intrinsically (as opposed to extrinsically) motivated actions (Rempel et al., 1985). This human-centered distinction has also been applied to AI contexts. For instance, Glikson and Woodley (2020) describe how tangibility and immediacy influence both types of trust in AI, whereby transparency, reliability and task characteristics shape cognitive trust, and anthropomorphism predicts emotional trust (Glikson & Woodley, 2020).

Understanding human trust provides valuable insights for human- computer interaction. Studies suggest that interaction with automation often follow norms similar to human interactions (Madhavan & Wiegmann, 2007). Users tend to trust AI systems more when they exhibit human-like characteristics, such as intentionality or rational behaviour, a phenomenon known as anthropomorphism (Glikson & Woodle, 2020; Gray et al., 2007; Waytz et al., 2014). AI systems in humanoid or pet-like form inspire more trust, while aggressive-looking systems impair trust (Siau & Wang, 2018). Despite the great similarity of trust in human-computer interaction, the process of building trust from human to human cannot be directly applied to trust from humans to computers (Madhavan & Wiegmann, 2007). The reliability of automation in certain tasks is the key factor in building trust in the machine (Fox, 1996). Previous research has shown that concepts of interpersonal trust can also be applied to the relationship between humans and technology, especially when the technology exhibits human characteristics (Calhoun et al., 2019; Gillath et al., 2021).

Trust in technology can be conceptualized along multiple dimensions, reflecting different aspects of users' perceptions and interactions. McKnight et al. (2011) distinguish trust in technology from human trust. While humans can act as moral agents, technical systems lack the capacity for independent decision-making and moral action. There are three dimensions of trust in technology, namely functionality, reliability and helpfulness. These dimensions are analogous to key aspects of trust in humans. Functionality refers to the performance of the technology and is compared to human capability. Reliability describes how consistently a system functions, which is like the concept of integrity. Helpfulness refers to the extent to which the technology provides benefits to users, comparable to the benevolence dimension of human trust (McKnight et al., 2011). Lee & See (2004) propose performance, process, and purpose as further dimensions. Performance refers to the ability of the technology to achieve the user's goal, which is reflected in competence or expertise. The process dimension is about whether the automation algorithm is appropriately designed to achieve the user's goal. The purpose dimension of trust describes why the technology was developed and whether it aligns with the user's goal. For algorithms and other automation technologies, it can be challenging to determine the right level of trust, specifically how much people believe in the reliability and accuracy of the technology's performance, which can impact the acceptance and effectiveness of the technology (Lee & See, 2004).

While these dimensions are applicable to AI, trust in AI requires additional consideration due to the unique characteristics of AI systems. Unlike general technology, AI lacks moral agency and volition, and its decision-making processes are often opaque, especially in machine learning systems (black box character), making it more difficult for users to understand how results are arrived at (Arrieta et al., 2020, Choung et al., 2022). Trust in AI is therefore influenced not only by functionality, reliability, and usefulness, but also by perceived transparency, explainability, and the role of human oversight in AI operations (Glikson & Woodly, 2020). This unpredictability emphasizes the need for trust when dealing with complex AI decision-making processes. Certain factors have been identified as key contributors to trustworthy AI systems. These include usefulness, performance, accuracy, and credibility, all of which strengthen the role of trust in the perception of AI attributes and promote user acceptance (Choung et al., 2022). For technologies that have more human-like factors, a scale of trust in humans is better at predicting relevant outcomes than a scale of trust in technology. This suggests that trust in technology is a dynamic concept that is still evolving and varies according to context and the characteristics of trustworthy agents (Lankton et al., 2015).

Lack of trust can impair collaboration, efficiency, and productivity (Braynov & Sandholm, 2002). Furthermore, lack of trust can hinder or prevent the integration of AI systems (Chakraborti et al., 2017) and generally inhibit the adoption of new technologies (Jeffries & Reed, 2000). The perception of risk must be overcome in order to create initial trust, which in turn promotes the willingness to use the technologies (McKnight et al., 2002). Beyond these general adoption barriers, the perception of fairness and trustworthiness also differs depending on whether decisions are made by humans or algorithms. The dynamics of trust also differ significantly between human managers and algorithms. The fairness and trustworthiness of a human manager are attributed to the manager's authority, while with algorithms, it is attributed to their perceived efficiency and objectivity. Human decisions lead to positive emotions due to possible social recognition, while algorithmic decisions tend to elicit mixed reactions. In human tasks, algorithmic decisions are perceived as less fair and trustworthy. The perceived lack of intuition and subjective judgment of algorithms contributes to the low trustworthiness ratings (Lee, 2018). Previous research on algorithms indicates mixed results in terms of acceptance. Some findings show that people trust algorithmic decisions more than human decisions (Madhavan & Wiegmann, 2007). Other research suggests that people trust their own judgement more, especially when the algorithm has made a mistake (Dietvorst et al., 2015).

Trust is an important prerequisite for the acceptance, introduction and use of technologies in general (Venkatesh et al., 2016) and for AI in particular (Siau & Wang, 2018). People are reluctant to let AI systems take over important decisions, “especially when this assistant makes decisions without providing a transparent rationale for choosing one solution over a range of alternatives” (Polonski, 2016, p. 1). Secondly, trust in such systems will be necessary for professionals to base their decisions on the systems’ predictions, classifications, and recommendations once they have been integrated into the decision-making process. In many cases, humans still have the ultimate power to decide how to deal with the results of AI. As people increasingly use AI to make, derive, and justify decisions, it is crucial to investigate under what conditions, in what ways, and for what reasons these systems are trusted or distrusted (Schmidt et al., 2020). This trust is particularly relevant for human-AI relationships, as they are perceived as involving risks due to the complexity and indeterminacy of AI behaviour and its future role in the workplace. AI is seen as a technology that will slowly take over different types of human jobs and fundamentally change the structure of organisations (Davis, 2019). In most cases, trust in humans increases over time due to frequent interactions, even though humans also make mistakes. In contrast, trust in technology often decreases over time, as errors and malfunctions are judged more harshly due to higher expectations of flawless performance (Madhavan & Wiegmann, 2007). The experiential aspect of AI technology is also very important in creating and maintaining trust. Users who have experience with a technology form an opinion of whether it is useful and easy to use based on their experience with it (Choung et al., 2022).

In their work, Choung et al. (2022) develop a two-pronged concept of trust in AI. They distinguish between trust in human-like aspects of AI, which primarily concerns the nature of the technology, and trust in AI's functionality, such as its performance, reliability, and security. For their study, they operationalize trust in AI through the dimension of humanness to capture automatic social cues, intentional action, and moral decisions, even though AI itself is not human. Both dimensions, the human and the functional, proved to be crucial predictors of the technology acceptance. Trust in AI is particularly crucial in high-risk application areas such as autonomous vehicles or medical decisions. In addition, Shin and Park (2019) showed that fairness, accountability, and transparency are crucial for user satisfaction with algorithms, where people with low trust in algorithmic decisions being particularly critical of these aspects.

While most research on trust in AI focuses on individual or organizational acceptance, the integration of AI also has broader societal implications that shape these dynamics indirectly. The integration of AI into the workforce is creating a complex landscape of opportunities and challenges that affect both society as a whole and specific organisational functions such as human resources. On a societal level, AI is reshaping the job market significantly. By creating new professional occupations related to AI, such as robotics specialists, data specialists and deep learning experts, new scenarios can be generated that can have a positive impact on society (Michailidis, 2018). A key problem in this area is the technological gap, as not all countries have the necessary resources to implement and operate AI infrastructure (Abdeldayem & Aldulaimi, 2020). Furthermore, the societal challenge is that the use of AI could lead to job losses in certain professions (Hamilton & Davison, 2022).

The study by Suseno et al. (2022) explores the willingness of HR managers to embrace the introduction of AI, with a particular focus on how their beliefs about AI, their anxiety regarding it, and their openness to change are shaped by different aspects of their attitudes. Grounded in the Tripartite Model of Attitudes (Eagly & Chaiken, 1993; Ajzen, 2005), the research examines attitudes as comprising three interrelated components: cognitive (thoughts and beliefs about AI), affective (emotions and feelings towards AI), and behavioural (intentions or actions related to AI adoption). Attitude itself is defined as a “psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour” (Eagly & Chaiken, 1993,

p. 1). In addition, the study examines the moderating role of high-performance work systems (HPWS) in the relationships between HR managers' beliefs, their AI-related uncertainty, and their willingness to change. HPWS promote the efficiency of workflows, strengthen employee performance and contribute to better overall organizational results. The results show that HR managers' beliefs about AI and their fear have a significant impact on their willingness to adopt AI. In particular, managers' beliefs positively influence their willingness to change, while AI fear negatively predicts their willingness to change. Furthermore, the results illustrate that HPWS can mitigate the negative effect of AI anxiety on HR managers' willingness to change when introducing AI (Suseno et al., 2022). By applying the TAM theory, the results of the study show that individual beliefs about AI (cognitive element) influence the willingness to change (behavioural element). An employee's AI anxiety (affective element) can also influence readiness (Rafferty & Jimmieson, 2017). The integration of both cognitive and affective elements contributes to the understanding of an individual's readiness to change (Rafferty & Minbashian, 2019). Madsen et al. (2005, p.216) identified in their study that an individual is ready for change "when he or she understands, believes, and has the intention to change because of a perceived need". In the case of organisations undergoing changes such as the adoption of AI, it is crucial to understand the readiness of members for such changes (Rafferty et al., 2013). The study by Suseno et al. (2022) highlights the importance of employees not only having the skills to work with AI, but also positive thoughts about the changes that will result from the use of AI.

Trust and Transparency in AI Systems in different HRM Functions

Trust can affect the use of AI in recruitment in various ways. The risk of bias in AI decisions affects trust in the fairness of the process. Adelmann & Wiedmer (2020), Dastin (2018) and Tambe et al. (2019) point out that the use of AI can lead to biases caused by errors in the amount of data on which the algorithm is based. Dastin (2018) reports on a specific case in which the use of algorithms in personnel selection led to biased decisions regarding gender and origin. The lack of traceability in AI-supported decisions can reduce the confidence of applicants. This is due to the black box nature of machine learning algorithms. It is very difficult for users to understand how these systems make decisions (Choung et al., 2022). AI systems are able to generate responses that copy human behaviour, but the underlying process of how exactly this happens is not explained (Arrieta et al., 2020).

To address these concerns and as the goal of this master’s thesis is to find out whether there are differences in trust in AI systems with regard to their areas of application, the following hypotheses are created:

H1: *Trust in AI recruitment tools has a positive effect on applicant acceptance of their use.*

This hypothesis posits that applicants trust in AI recruitment tools directly influences their willingness to engage with these systems. Previous research supports this notion, indicating that trust is a critical factor in technology acceptance (McKnight et al., 2011).

H2: *The relationship between perceived ease of use of AI recruitment tools and applicant acceptance of these tools is moderated by trust in AI systems.*

This hypothesis is based on the extended Technology Acceptance Modell (TAM2), which incorporates trust as a moderating factor between perceived ease of use und technology acceptance (Venkatesh & Bala, 2020). In this study, this mechanism is applied specifically to AI- based recruitment contexts, where trust has not yet been systematically tested as a moderator.

To visualize the relationships proposed in H1 and H2, the following conceptual model (Figure 2) is presented. The arrows in the model indicate the direction of the hypothetical relationships and their expected effects. It is expected that trust in AI recruitment tools will have a positive influence on applicant acceptance, meaning that higher trust directly increases applicants' willingness to engage with these systems, as outlined in H1. In addition, it is expected that the perceived ease of use of AI recruitment tools will also positively influence applicant acceptance. This relationship is moderated by trust in AI systems, such that higher levels of trust amplify the positive effect of perceived ease of use on acceptance, as formulated in H2. Overall, the model shows directed, positive relationships that reflect the theoretical logic and empirical evidence for these hypotheses.

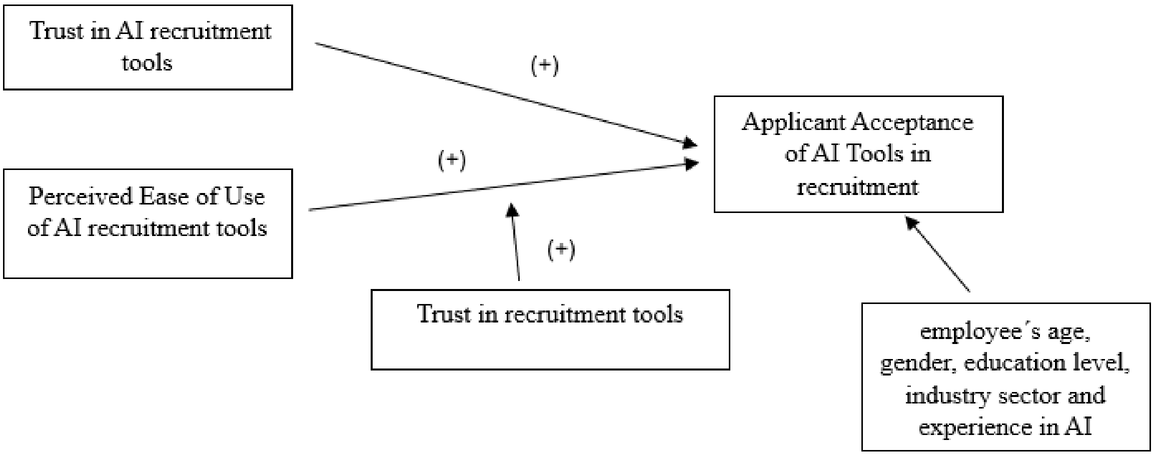

Figure 2 Research Design Hypotheses 1 and 2

H3: *Trust in AI is a significant predictor of applicant acceptance of AI selection tools.*

This hypothesis distinguishes between trust in recruitment tools (focused on fairness and transparency) and trust in selection tools (centred on the accuracy and reliability of the assessments). Glikson & Woodley (2020) argue that trust in AI systems is context- dependent, varying across different HRM functions. Studies show that applicants trust in AI selection tools positively impacts their willingness to comply with AI- driven assessments and accept results (Tambe et al., 2019), further empirical testing is required to disentangle the different roles trust plays in recruitment versus selection.

Figure 3 illustrates the research design für H3, which posits that trust in AI selection tools is a significant predictor of applicant acceptance. The model visualizes the hypothesized positive relationship, indicating higher trust in AI selection tools is expected to increase applicants' willingness to engage with these tools.

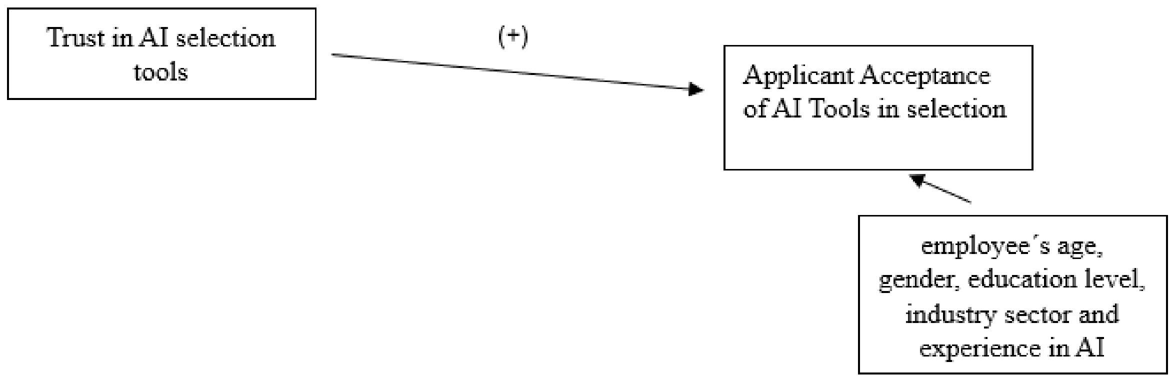

Figure 3 Research Design Hypothesis 3

In the area of training & development, trust in AI may differ from trust in recruitment and selection tools, reflection specific functions and expectations associated with these HR processes. The distinction is supported by research indicating that employees often perceive AI applications in training & development as more supportive and less intrusive compared to those in recruitment. For instance, a study by Sadeghi (2024) highlights that while AI can enhance efficiency and reduce bias in recruitment, it also raises concerns about job security, fairness and privacy. In contrast, AI in training is generally viewed more positively, as it is perceived to offer personalized learning experiences and professional development opportunities without the immediate pressure of hiring decisions (Sadeghi, 2024).

The personalisation of learning programs and the resulting individualized learning content can strengthen trust in AI through perceived effectiveness. The study by Pillai et al. (2020) underlines that personalised AI-supported learning programs can increase perceived effectiveness and thus trust in the technology. Hamilton & Davison (2022) and Nankervis et al. (2021) also confirm this correlation in their works. AI has the ability to analyse learning progress and adapt content, accordingly, resulting in continuous improvement that can increase trust in the technology. While Nankervis et al. (2021) emphasize the organisational benefits of AI in terms of efficiency and accuracy in HR processes, these improvements are directly experienced by employees through more targeted and effective training interventions, which in turn shape their trust in AI applicants. By using machine learning, data can be continuously analysed, and conclusions can be derived (Hamilton & Davison, 2022).

Based on the Technology Acceptance Model (Venkatesh & Davis, 2000) and its extensions that integrate trust as both direct and moderating factor (Gefen et al., 2003; Venkatesh & Bala, 2008), trust in AI therefore expected to play a dual role in employee acceptance of AI- based training tools: as a direct contributor to acceptance and as a moderator of perceived ease of use. While previous research has demonstrated the positive influence of personalization and perceived usefulness on acceptance in training contexts (Hamilton & Davison, 2022), the specific moderating role of trust in AI tools for training and development remain underexplored. From these assumptions, the following hypotheses are derived:

While recruitment and selection focus on applicants trust in AI, the context of training and development naturally involves employees who are already part of the organisation. Therefore, the following hypotheses address employees trust in AI applications within training and development.

H4: *Both the perceived ease of use and trust in AI systems make a significant contribution to explaining employee acceptance of AI tools in training & development.*

H5: *The relationship between perceived ease of use of AI tools in training & development programs and employee acceptance of these tools is moderated by trust in AI.*

Figure 4 shows the research model for H4 and H5 in the context of AI-supported training and development. The figure shows that both perceived ease of use and trust in AI systems have a direct positive influence on the acceptance of these tools by employees (H4). Furthermore, trust in AI acts as a moderating factor on the relationship between perceived ease of use and acceptance (H5), suggesting that the strength of this effect varies depending on the degree of trust employees have in the system.

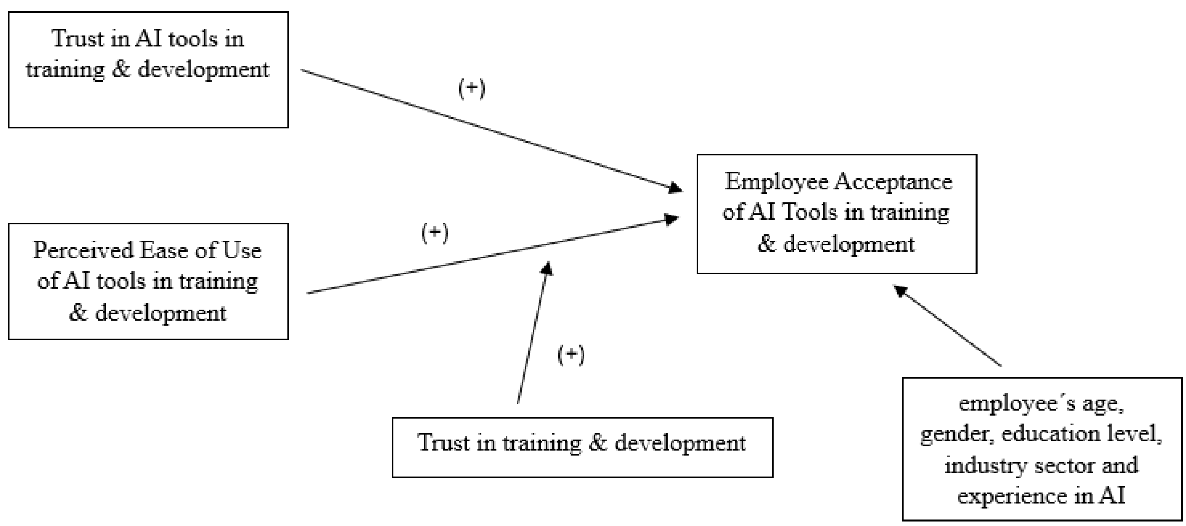

Figure 4 Research Design Hypotheses 4 and 5

As applicant data is sensitive data, there may be data protection concerns on the part of applicants and mistrust may arise. In their paper, Tambe et al. (2019) address the various ethical concerns that can arise from the use of AI in HRM. The authors point out that the use of AI in recruitment raises questions about data protection and privacy, which can lead to mistrust on the part of applicants (Tambe et al., 2019). Bankins (2021) also addresses this issue in her paper on whether the use of AI is appropriate in areas that directly involve the management of sometimes sensitive aspects of the employee lifecycle. The following hypothesis can be used to test data sensitivity:

H6: *Trust in AI systems significantly influence applicants' acceptance of AI in the HRM context.*

In this study, general trust and general acceptance are conceptualized as overarching constructs derived from the specific dimensions of recruitment, selection, and training and development. This approach is supported by research on trust in information systems, which shows that trust can be both context-specific and cross-cutting, reflecting general trust in technology (Gefen et al., 2003, McKnight et al., 2011). Similarly, the acceptance of HR technologies can be viewed holistically, as applicants and employees often experience these systems as part of an integrated HR ecosystem rather than as isolated applications (Strohmeier, 2020). By aggregating these areas, the hypothesis captures the broader impact of trust on AI acceptance across HRM functions, rather than limiting the analysis to a single context.

Figure 5 visualizes the hypothetical relationship for H6 and shows that the acceptance of AI in the HRM context is directly influenced by applicants' trust in AI systems. The relationship between trust in AI systems and applicant acceptance shows a positive effect, suggesting that greater trust is likely to increase acceptance in all HRM functions. This figure focuses on the overarching influence of general trust and combines insights from the areas of recruitment, selection, and training and development into a single conceptual path.

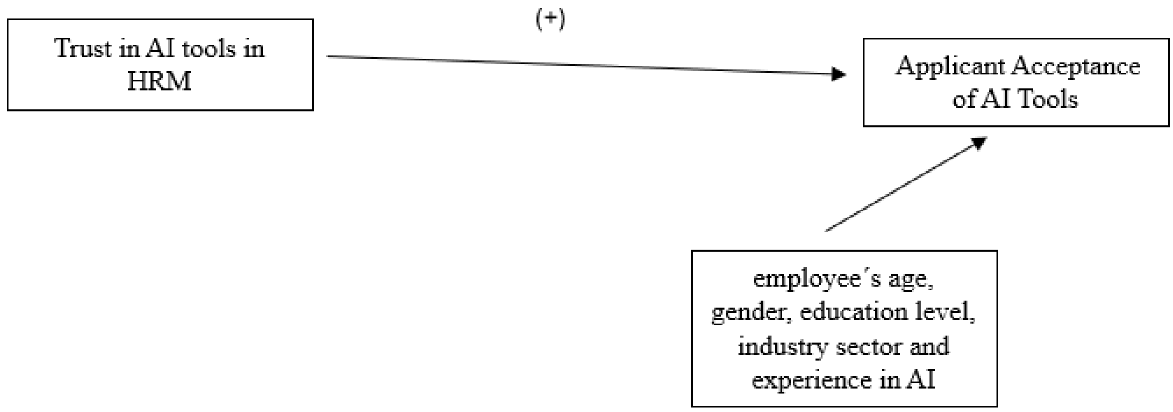

Figure 5 Research Design Hypothesis 6

Compared to recruitment, less sensitive personal data is processed in training & development, which can lead to fewer data protection concerns. In their paper, Strohmeier & Piazza (2015) discuss the use of AI technologies in various HRM areas and the resulting differences in data protection requirements. The study by Cheng & Hackett (2021) also compares different areas concerning the use of algorithms and discusses the different data protection implications.

There are still some factors that are of great importance in both areas. These include transparency about AI processes and a clear ethical framework. Another important factor is human control. The perception that humans are monitoring AI systems can promote trust in both areas.

3. Methodology

There are two different approaches for the methodological part, namely a quantitative and a qualitative approach. Quantitative research refers to the quantification of facts, large samples, representativeness, linear processes, and standardized procedures. It is interested in objective facts and is more akin to laboratory research. In contrast, the qualitative approach stands for understanding meaning, looking at individual cases, interest in subjective facts, and field research. Quantitative methods include, for example, surveys and experiments, while qualitative methods include long and non-standardized interviews (Eisend & Kuß, 2021). The orientation of qualitative research is explorative, reconstructive, and strictly inductive, while quantitative research can pursue explanatory as well as explorative knowledge objectives by testing hypotheses (Boßow-Thies & Krol, 2022).

Empirical data can be collected using different scientific methods, whereby the form of data collection and the nature of the data determine the data analysis (Kaya, 2009).

In qualitative research, non-numerical data is analysed and interpreted to explore an issue, answering the research question posed and generating a new theory or hypothesis. This approach is characterised by openness to new results and a high degree of flexibility, which is also evident in the iterative research process. One advantage of qualitative research is that individual cases can be intensively analysed, and thus realistic data can be generated. The weaknesses of this type of research point to the non-generalisability of the results, a high time expenditure, and strong subjectivity. An important point is that qualitative research is used to formulate hypotheses, which are then tested using quantitative research (Boßow-Thies & Krol, 2022).

Quantitative research is more explanatory, descriptive, and deductive in nature and numerical data is analysed statistically with a focus on the research question. The main objectives are primarily to test the hypotheses, theories, quantification, and generalisability of the results. The strengths of quantitative research lie in the objectivity, comprehensibility, comparability, and credibility of studies as well as in the possible generalisability and predictability of results (Boßow-Thies & Krol, 2022). The weaknesses lie in confirmation bias, a distortion that results from the tendency to search for information and evidence that fulfills one's expectations, as well as in the possibly high degree of abstraction of the results (Johnson & Onwuegbuzie, 2004; Nickerson, 1998).

The strengths of qualitative and quantitative research approaches can be combined with a simultaneous equalisation of the respective weaknesses within the framework of a mixed-method approach in order to achieve a greater gain in knowledge (Johnson & Onwuegbuzie, 2004).

The data used can be qualitative (nominal or ordinal scaled) or quantitative (interval or ratio scaled). This distinction is of fundamental importance for the interpretation and further processing of the data. The measurement or scale levels should therefore always be taken into account for all measurements (Oehlrich, 2022).

Quantitative research aims to record empirical experiences as figures for as large a population as possible to analyse them using statistical methods such as hypothesis testing or regression analysis. The data collected is regarded as (largely) objective characteristics of reality. In the case of quantitative data, data evaluation always follows the same pattern, namely the data is first subjected to descriptive analysis, whereby the underlying distribution is characterised by location and dispersion parameters (e.g. arithmetic mean, median, ...) before the concluding statistics (hypothesis test, regression analysis) follow (Oehlrich, 2022). Quantitative research begins with operationalisation, sampling, and data collection. This is followed by data preparation/analysis and interpretation of the results, and finally the presentation of the results (Boßow-Tiel & Krol, 2022).

In comparison, qualitative research deals with subjective reality, namely the individual view of certain people. In this case, the data is not analysed with emotional distance to the data providers, but with clear proximity and openness toward the people being researched. The methods for analysing data are more heterogeneous in qualitative research. This includes qualitative content analysis and other methods of empirical social research (Oehlrich, 2022). The process of qualitative research begins with sampling, data collection, data preparation/analysis, and interpretation of results. This is followed by hypothesising and theorising and then the presentation of results (Boßow-Tiel & Krol, 2022).

In many areas of economics, there has been a trend towards quantitative research, particularly in recent decades, which ensures the corresponding objectivity. The development in this direction is also driven by the fact that the top journals in economics show a preference for quantitative research. The use of purely qualitative, verbal sources such as interviews is no longer very important in empirical research in economics if they are not systematically analysed using scientific methods such as qualitative content analysis (Oehlrich, 2022).

This study employed a quantitative online survey method. This method was chosen because it allows for efficient and systematic data collection from a geographically diverse sample while ensuring high levels of respondent anonymity and data quality (Evans & Mathur, 2005; Wright, 2005). Online surveys are particularly suitable for research on trust in AI systems, as they enable respondents to interact with hypothetical or simulated AI scenarios without social pressure, thereby reducing potential bias and encouraging honest reporting of perceptions and attitudes (Fan & Yan, 2010). Moreover, this method aligns well with the study's focus, as it enables the testing of hypotheses, theories, and the generalizability of results. In this context, the strengths of quantitative research—objectivity, comparability, and credibility—are particularly relevant (Boßow-Thiel & Krol, 2022). Additional advantages and objectives have already been outlined above. Since no suitable secondary data was available, as demonstrated in the literature review, a primary survey was conducted to address the research question and test the hypotheses, which were derived from previous research findings.

The hypotheses in this study are based on the Technology Acceptance Model (TAM) as the theoretical foundation. The dependent variable is acceptance of different AI application areas, specifically applicant acceptance in recruitment and selection, and employee acceptance for training & development. Since the questionnaire does not contain any direct items on usage intention or actual usage, operationalization is based on perceived usefulness. Perceived usefulness is a central component of TAM and is considered one of the strongest predictors of actual acceptance and usage intention (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Numerous studies have used perceived usefulness as a proxy for acceptance, as it not only reflects perceived usefulness but is also closely linked to behavioural intentions and actual use (King & He, 2006; Marangunic & Garnic, 2015). Accordingly, in this study, employee acceptance is operationalized using items on perceived usefulness that were adapted from the original scale by Davis (1989). The independent variables correspond to the specific constructs relevant to each HRM function: trust in AI recruitment tools, perceived ease of use of AI recruitment tools, trust in AI selection tools, perceived ease of use and trust in AI tools for training and development, and trust in AI systems in HRM in general.

In the TAM- based model applied in this study, trust functions as a moderator for H2 and H5. The choice of trust as moderating variable follows directly from the hypothesis's development, where it was argued based on TAM2 and prior research (Choung et al., 2022; Gefen et al., 2003; McKnight et al., 2011; Venkatesh & Bala, 2008) that trust can influence the strength of the relationship between perceived ease of use and AI acceptance. The control variables are employees' age, gender, education level, industry sector, and experience with AI. The relationship between the dependent and independent variable is influenced by a moderator variable, meaning that the effect of the independent variable on the dependent variable can be stronger or weaker depending on the moderator's impact. In contrast, mediator variables explain indirect relationships between variables. A mediator clarifies the mechanism through which an independent variable affects a dependent variable (Eisend & Kuß, 2021).

These correlations arise from previous research, such as the paper by Gefen et al. (2003), that the paths predicted by TAM also apply to e-commerce. This research is based on the same logic, highlighting that perceived ease of use and perceived usefulness are critical determinants of technology adoption, except that it is about AI systems. Translating this logic to AI systems, the more employees or applicants perceive an AI tool as easy to interact with (intuitive interface, clear instructions) and useful (supporting task completion efficiently), the more likely they are to adopt and use it (Choung et al., 2022; Gefen et al., 2003). The role of trust as a predictor of technology adoption has been well- established in prior studies, including, the use of a new information system (Tung et al., 2008) and shopping platforms (Gefen et al., 2003. A meta-analysis showed that trust has a significantly positive influence on the most important TAM constructs (Wu et al., 2011), strengthening the argument that trust is crucial for AI acceptance in HRM contexts.

This study applies TAM with trust as a direct and moderating factor specifically to AI systems in HRM functions. In contrast to previous studies that focus on e-commerce or general information systems, this study compares several HRM functions (recruitment, selection, and training and development) and considers both the perspective of applicants and that of employees, depending on the function. This approach allows for a differentiated view of trust and acceptance in organizational contexts. This makes it possible to capture the nuanced effects of trust in various areas of human resource management that have not yet been systematically investigated in previous studies (Choung et al., 2022; Glikson & Woodley, 2020).

Data Collection Method

Data were collected using the online survey platform Qualtrics. Potential participants received an invitation to the questionnaire by email or via social media (Facebook, WhatsApp). The survey phase lasted from 21 March 2025 to 16 April 2025.

Before the start of the survey, the questionnaire was evaluated with the help of 10 pretests with regard to applicability, completeness, quality, and duration. The feedback from the pretest participants was used solely to refine the questionnaire and was not included in the main dataset. Some areas were modified slightly based on the feedback provided by the pre-test participants. For example, the explanation at the beginning is that the questionnaire is divided into three segments in order to achieve a better understanding for the participants (see full survey form in Appendix A).

At the beginning of the study, the topic is introduced, highlighting its importance and providing context for the questions. Participants are asked to imagine themselves as job seekers using various AI-powered tools and systems throughout the application process. It is emphasized that responses should be given from the perspective of an applicant or new employee. This approach was chosen because not all participants may currently be applying for jobs or actively engaged in a work environment. By asking them to adopt a hypothetical perspective, the study ensures that all respondents can provide meaningful answers, regardless of their current employment or application status. This approach follows the logic of prior TAM and trust studies, where hypothetical scenarios are used to measure perceptions of technology among participants who may not have current experience (Gefen et al., 2003; McKnight et al., 2011).

The main part of the survey is structured into three key sections, followed by demographic questions. The first section focuses on the use of AI in recruitment, the second on its role in candidate selection, and the third on its application in training & development. The questions explore how participants' confidence in these technologies may vary depending on different influencing factors.

The survey was designed to capture participants perceptions across recruitment, selection, and training and development. To ensure that these perceptions accurately reflect the underlying theoretical constructs, such as trust in AI systems and perceived ease of use, these concepts must be operationalised. The constructs “Trust” and “Perceived Ethical Considerations” were conceptually very similar, both relating to confidence in AI systems and ethical use of personal data. Therefore, the survey items from these two categories were combined and only three separate variables one for each HRM area were created. This approach ensures that the construct is clearly defined and operationalised. Operationalisation allows abstract constructs to be translated into measurable variables that can be analysed statistically (Boßow- Thiel & Krol, 2022; Eisend & Kuß, 2021). This involves assigning concrete measurement procedures to theoretical constructs. In other words, the theoretical concepts are assigned observable facts that relate to the variables. A variable is a specific characteristic or behaviour of objects. The application of the selected procedures and the corresponding parts of reality are referred to as measurement. This process is two-sided because the test subjects or objects are confronted with the measuring instruments and measured values (data) flow back. The aim of the measurement is a structured transfer of an empirical relationship into a numerical relationship (Eisend & Kuß, 2021). They can be observed and measured either directly (manifest) or not directly (latent). A directly measurable construct is, for example, turnover, which is clearly defined. In the case of non-directly measurable variables, such as trust, there are different definitions, which also entail different operationalisations. If there are validated constructs that have already been measured many times, such as trust, then the operationalisation should be adopted from previous studies. If necessary, it must be adapted to the present study context (Boßow-Tiel & Krol, 2022).

The generalisability or representativeness and transferability of the results to different contexts and objects is an important point. For representativeness to be guaranteed, all study units must have either the same or at least a previously known probability of being selected. This point can best be guaranteed by random line sampling (Eisend & Kuß, 2021).

Validity and reliability are criteria for checking the quality of the measurement instruments and are checked using established statistical procedures. Validity refers to the avoidance of systematic deviations of the test result from the true value. Reliability refers to the independence of a test result from a one-off measurement process influenced by randomness (Eisend & Kuß, 2021).

The answers to the questions are measured using a 5-point Likert scale (1 - strongly disagree / 5 - strongly agree). The items in the survey relate to the TAM construct, which was explained in more detail in the theoretical framework section, and to the constructs used to measure trust.

At the end of the survey, some demographic questions are asked to be able to make statements about which gender, age, and education lead to the results.

The following table shows how the different items are operationalised and measured.

Construct	Original Scale	Survey Items	Comments	Source	Cronbach´s Alpha
Applicant Acceptance of AI Recruitment Tools	*Q1: My job would be difficult to perform without electronic mail.* *Q2: Using electronic mail gives me greater control over my work.* *Q3: Using electronic mail improves my job performance.* *Q4: The electronic mail system addresses my job- related needs.* *Q5: Using electronic mail saves me time.* *Q6: Electronic mail enables me to accomplish tasks more quickly.* *Q7: Electronic mail supports critical aspects of my job.* *Q8: Using electronic mail allows me to accomplish more work than would otherwise be possible.* *Q9: Using electronic mail reduces the time I spend on unproductive activities.* *Q10: Using electronic mail enhances my effectiveness on the job.* *Q11: Using electronic mail improves my quality of the work I do.* *Q12: Using electronic mail increases my productivity.* *Q13: Using electronic mail makes it easier to do my job.* *Q14: Overall, I find the electronic mail system useful for my job.*	Q1: Using AI-based tools in recruitment systems would improve my job application process. Q2: AI-based tools in recruitment systems would enable me to accomplish job application tasks more quickly. Q3: AI-based tools in recruitment systems would support me with job search activities. Q4: Using AI-based tools during my job search would reduce the time I spend on unproductive activities.	These questions were inspired by Davis' original scale (1989) but adapted to the context of applicants and AI-supported recruitment systems. The selection focuses on perceived usefulness and efficiency, while aspects relevant to permanent employees have been excluded. In this study, perceived usefulness serves as the operationalisation of the construct Applicant Acceptance consistent with TAM literature.	Davis, 1989	0,97

Construct	Original Scale	Survey Items	Comments	Source	Cronbach´s Alpha
Perceived Ease of Use of AI Recruitment Tools	*Q1: Learning to use (AI virtual assistants/ AI smart technologies) would be easy for me.* *Q2: I would find it easy to get (AI virtual assistants/ AI smart technologies) to do what I want it to do.* *Q3: My interaction with (AI virtual assistants/ AI smart technologies) is clear and understandable.* *Q4: It would be easy for me to become skillful at using (AI virtual assistants/ AI virtual technologies).* *Q5: I would find (AI virtual assistants/ AI smart technologies) to be easy to use.*	Q1: As a job applicant, I would find it easy to use AI-based tools for job searching. Q2: I would find it easy to navigate AI-powered job application systems. Q3: My interaction with AI-powered chatbots and interfaces would be clear and understandable. Q4: It would be easy for me to become proficient at using AI-driven job search and application platforms.	I chose these questions because they best capture the perceived ease of use of AI-supported recruitment systems and are directly applicable to the application process. Other questions from the original questionnaire were omitted as they relate more to general AI use and are less relevant to my research focus.	Choung et al., 2022	0,90

Construct	Original Scale	Survey Items	Comments	Source	Cronbach´s Alpha
Trust in AI Recruitment Tools (including perceived Ethical Consideration in AI recruitment tools)	*Q1: The system is deceptive.* *Q2: The system behaves in an underhanded manner.* *Q3: I am suspicious of the system´s intent, action, or output.* *Q4: I am wary of the system.* *Q5: The system´s actions will have a harmful or injurious outcome.* *Q6: I am confident in the system.* *Q7: The system provides security.* *Q8: The system has integrity.* *Q9: The system is dependable.* *Q10: The system is reliable.* *Q11: I can trust the system.* *Q12: I am familiar with the system.*	Q1: I can trust AI systems used by recruiters in the job posting and application process. Q2: I am confident in the decisions made by AI systems used in identifying and attracting potential job candidates. Q3: I am suspicious of the intent or output of AI systems used by recruiters in job posting and candidate sourcing processes.	This construct combines items from the Trust Scale and the Perceived Ethical Considerations Scale, as both aspects are closely related to the overarching concept of trust in AI systems. The ethical items complement trust with aspects of data protection and fairness, creating a consistent and theoretically sound measure of the trustworthiness of AI in the HRM context. Item Q3 is coded inversely, so that a higher value reflects greater trust in AI systems, consistent with the other trust items.	Jian et al., 2000	0,85
	Q1: I trust that AI virtual assistants can offer information and service that´s best of my interest. *Q2: I trust that my personal data is protected from potential abuse when using AI virtual assistants.* *Q3: I trust that my personal data is protected when using AI virtual assistants.* *Q4: I trust that my privacy is protected when using AI virtual assistants.* *Q5: I trust that authorities exerts effective control over organizations and companies providing AI virtual assistants service.*	Q4: I trust that my personal data is protected when AI-based tools are used in the recruitment process. Q5: I trust that companies providing AI systems for recruitment purposes comply with ethical and legal standards.		Choung, 2022	0,81

Construct	Original Scale	Survey Item	Comments	Source	Cronbach´s Alpha
Applicant Acceptance of AI Selection Tools	*Q1: My job would be difficult to perform without electronic mail.* *Q2: Using electronic mail gives me greater control over my work.* *Q3: Using electronic mail improves my job performance.* *Q4: The electronic mail system addresses my job- related needs.* *Q5: Using electronic mail saves me time.* *Q6: Electronic mail enables me to accomplish tasks more quickly.* *Q7: Electronic mail supports critical aspects of my job.* *Q8: Using electronic mail allows me to accomplish more work than would otherwise be possible.* *Q9: Using electronic mail reduces the time I spend on unproductive activities.* *Q10: Using electronic mail enhances my effectiveness on the job.* *Q11: Using electronic mail improves my quality of the work I do.* *Q12: Using electronic mail increases my productivity.* *Q13: Using electronic mail makes it easier to do my job.* *Q14: Overall, I find the electronic mail system useful for my job.*	Q1: I believe AI selection tools used by employers would effectively address my need to find job opportunities matching my skills and qualifications. Q2: I believe employers' use of AI selection tools would save me time during the job application process. Q3: I believe employers' use of AI selection tools would improve the quality of feedback I receive during the job application process. Q4: I believe employers' use of AI selection tools would enhance my overall experience in the job application process.	These questions were inspired by Davis' original scale (1989) but adapted to the context of applicants and AI-supported selection systems. The selection focuses on perceived usefulness and efficiency, while aspects relevant to permanent employees have been excluded. In this study, perceived usefulness serves as the operationalisation of the construct Applicant Acceptance consistent with TAM literature.	Davis, 1989	0,97

Construct	Original Scale	Survey Item	Comments	Source	Cronbach´s Alpha
Trust in AI Selection Tools (including Perceived Ethical Consideration in AI Selection Tools)	*Q1: The system is deceptive.* *Q2: The system behaves in an underhanded manner.* *Q3: I am suspicious of the system´s intent, action, or output.* *Q4: I am wary of the system.* *Q5: The system´s actions will have a harmful or injurious outcome.* *Q6: I am confident in the system.* *Q7: The system provides security.* *Q8: The system has integrity.* *Q9: The system is dependable.* *Q10: The system is reliable.* *Q11: I can trust the system.* *Q12: I am familiar with the system.* *Q1: I trust that AI virtual assistants can offer information and service that´s best of my interest.* *Q2: I trust that my personal data is protected from potential abuse when using AI virtual assistants.* *Q3: I trust that my personal data is protected when using AI virtual assistants.* *Q4: I trust that my privacy is protected when using AI virtual assistants.* *Q5: I trust that authorities exerts effective control over organizations and companies providing AI virtual assistants service.*	Q1: I can trust AI systems used by recruiters when evaluating my application and qualifications during the candidate selection process. Q2: I am confident in the decisions made by AI systems when recruiters use them to evaluate my application during the candidate selection process. Q3: I am suspicious of the intent or output of AI systems used by recruiters to evaluate my application during the candidate selection process. Q4: I trust that my personal data is protected when recruiters use AI systems in the candidate selection process. Q5: I trust that companies providing AI systems for candidate selection purposes comply with ethical and legal standards.	This construct combines items from the Trust Scale and the Perceived Ethical Considerations Scale, as both aspects are closely related to the overarching concept of trust in AI systems. The ethical items complement trust with aspects of data protection and fairness, creating a consistent and theoretically sound measure of the trustworthiness of AI in the HRM context. Item Q3 is coded inversely, so that a higher value reflects greater trust in AI systems, consistent with the other trust items.	Jian et al., 2000 Choung, 2022	0,85 0,81

Construct	Original Scale	Survey Item	Comments	Source	Cronbach´s Alpha
Employee Acceptance of AI in training & development	*Q1: My job would be difficult to perform without electronic mail.* *Q2: Using electronic mail gives me greater control over my work.* *Q3: Using electronic mail improves my job performance.* *Q4: The electronic mail system addresses my job- related needs.* *Q5: Using electronic mail saves me time.* *Q6: Electronic mail enables me to accomplish tasks more quickly.* *Q7: Electronic mail supports critical aspects of my job.* *Q8: Using electronic mail allows me to accomplish more work than would otherwise be possible.* *Q9: Using electronic mail reduces the time I spend on unproductive activities.* *Q10: Using electronic mail enhances my effectiveness on the job.* *Q11: Using electronic mail improves my quality of the work I do.* *Q12: Using electronic mail increases my productivity.* *Q13: Using electronic mail makes it easier to do my job.* *Q14: Overall, I find the electronic mail system useful for my job.*	Q1: Using AI systems would enhance my performance in training & development. Q2: AI systems would enable me to complete training & development tasks more efficiently. Q3: AI systems would enhance my training & development activities.	These questions were inspired by Davis' original scale (1989) but adapted to the context of applicants and AI-supported training and development systems. The selection focuses on perceived usefulness and efficiency, while aspects relevant to permanent employees have been excluded. In this study, perceived usefulness serves as the operationalisation of the construct Employee Acceptance consistent with TAM literature.	Davis, 1989	0,97

Construct	Original Scale	Survey Item	Comments	Source	Cronbach´s Alpha
Trust in AI Tools in training & development (including Perceived Ethical Consideration in AI Tools in training & development)	*Q1: The system is deceptive.* *Q2: The system behaves in an underhanded manner.* *Q3: I am suspicious of the system´s intent, action, or output.* *Q4: I am wary of the system.* *Q5: The system´s actions will have a harmful or injurious outcome.* *Q6: I am confident in the system.* *Q7: The system provides security.* *Q8: The system has integrity.* *Q9: The system is dependable.* *Q10: The system is reliable.* *Q11: I can trust the system.* *Q12: I am familiar with the system.*	Q1: I can trust AI systems used in my training & development activities. Q2: I am confident in the decisions made by AI systems used in planning and implementing my training & development activities. Q3: I am suspicious of the intent or output of AI systems used in my training & development activities.	This construct combines items from the Trust Scale and the Perceived Ethical Considerations Scale, as both aspects are closely related to the overarching concept of trust in AI systems. The ethical items complement trust with aspects of data protection and fairness, creating a consistent and theoretically sound measure of the trustworthiness of AI in the HRM context. Item Q3 is coded inversely, so that a higher value reflects greater trust in AI systems, consistent with the other trust items.	Jian et al., 2000	0,85
	Q1: I trust that AI virtual assistants can offer information and service that´s best of my interest. *Q2: I trust that my personal data is protected from potential abuse when using AI virtual assistants.* *Q3: I trust that my personal data is protected when using AI virtual assistants.* *Q4: I trust that my privacy is protected when using AI virtual assistants.* *Q5: I trust that authorities exerts effective control over organizations and companies providing AI virtual assistants service.*	Q4: I trust that my personal data is protected when AI systems are used in my training & development activities. Q5: I trust that companies providing AI systems for training & development purposes comply with ethical and legal standards.		Choung, 2022	0,81

Table 2 Survey Questions

The items for the survey were adapted from their original versions. The adaptions primarily involve changing the context from robots, electronic mail, websites, or other technologies to AI systems in HRM contexts.

The Cronbach´s Alpha values reported in Table 2 are from the original scales in the cited sources. For adapted items or scales where only some items are selected, these Cronbach´s Alpha values represent the reliability of the complete original scale, not the adapted or partial version used in this study. The reliability of the adapted versions will be calculated and reported in the empirical part of the thesis.

The questionnaire by Davis (1989) was originally developed as part of the Technology Acceptance Model (TAM) and therefore provides a solid basis for measuring perceived usefulness, which in this study serves as an indicator of applicant/employee acceptance of AI-supported systems. With a proven reliability of 0.97, the questionnaire demonstrates its reliability for measurements. When factor analysing the items, the factor loadings for perceived usefulness typically have values of 0.70 to 0.90, indicating that the items have a strong correlation with the construct's perceived usefulness and are therefore well suited to measuring this construct (Davis, 1989). The constructs measured in the Davis (1989) questionnaire were used in many later studies, sometimes in a modified or reduced form. The basic concept and the scales used are widely used in research, particularly in the field of technology and IT user acceptance. Building on the original TAM by Davis (1989), Venkatesh and Davis (2000) developed the TAM2 model, which expands on the original questions and includes additional variables. In the study by Venkatesh et al. (2003), elements of the TAM model were also included, and a new model was created from them. To measure the acceptance of online shopping, the questionnaire by Davis (1989) was used, whereby elements of the model were extended to include the trust factor (Gefen et al., 2003). In the studies by Tarhini et al. (2015) and King and He (2006), the original constructs were adapted to the respective context. Venkatesh & Bala (2008) extended the TAM model with additional constructs and created the TAM3 model.

In their study, Choung et al. (2022) developed a questionnaire that measures trust in AI, perceived usefulness, and perceived ease of use and is therefore suitable for the survey in this master's thesis. In this study, perceived usefulness is used as an indicator of applicant/employee acceptance of AI- supported systems. The questions in the questionnaire were developed based on existing TAM models and similar models of technology acceptance but specifically tailored to the context of AI systems. The reliability of 0.81 to 0.90 is also very high and shows the reliability of the questionnaire. Most factor loadings are also above 0.80, which indicates a strong correlation between the items and the construct (Choung et al., 2022). According to Google Scholar, the article has already been cited 399 times, but it is not specified whether the questionnaire or the results of the study are cited.

The study by Jian et al. (2000) deals intensively with the topic of trust in technology. It examines various dimensions of trust, including the reliability, security, integrity, and privacy of automated systems. These aspects are also relevant for measuring trust in AI and for this reason, the questions can be applied to the survey of this work. With a Cronbach's alpha of 0.85, the reliability of this questionnaire is high and thus demonstrates the reliability of the measurements. The factor loadings are above 0.7 for most items, which indicates a strong correlation. The operationalised constructs from the study by Jian et al. (2000) have been reused in numerous studies, often in modified or shortened form to meet specific research requirements. One example of this is the study by Spain et al. (2008). The researchers conducted an exploratory factor analysis of the original questionnaire. In the study by Kohn et al. (2021), the researchers investigated different methods of measuring trust and the questionnaire by Jian et al. (2000) was identified as a commonly used instrument. Perrig et al. (2023) validated the constructs of Jian et al. (2000) in the context of human-AI interactions and confirmed the relevance of current research questions. These examples show that the items from the Jian et al. (2000) study have been reused in other areas and their relevance to current studies has also been confirmed.

4. Empirical Analysis

This section outlines the empirical study and presents the findings of the quantitative data analysis, performed using STATA software.

The results of the study were exported from the Qualtrics platform in the form of an Excel file and a few adjustments were made, such as removing the start date or the duration of the survey, so that the focus is on the variables that are important for answering the hypotheses. A total of 236 participants started the survey, but not all participants answered the entire survey. The number of valid responses was between 109 and 121. During data preparation, incomplete or irrelevant entries were excluded, ensuring that the final analyses were based only on valid observations.

In order to create variables from the individual questions, a few of the questions always had to be combined to form a complete variable. The questions from the respective construct were combined for each item. To finally be able to analyse the hypotheses, variables had to be created for acceptance in recruitment, selection, and training & development. This process is based on the Technology Acceptance Model (TAM). As explained in the Methodology section, behaviour- related items from the perceived usefulness scale were used as indicators for applicant/employee acceptance to ensure a clear distinction between independent and dependent variables to maintain construct validity (Venkatesh & Davis 2000).

The variables used in this study contain several scales where missing values may be unavoidable, manual handling of missing values was not used. Instead, the functionality of STATA was used to ensure that only valid data was included in the calculations and analyses. It was automatically controlled by STATA when creating new variables and performing different tests. This is because STATA automatically excludes missing values for most commands. This means that when calculating variables such as the mean value of several items (rowmean), only valid (not missing) values are considered.

4.1 Descriptive Statistics

At the beginning of the analysis, the sample was analysed in more detail.

Firstly, here are charts showing the distribution of age, gender, education, background, and experience in AI.

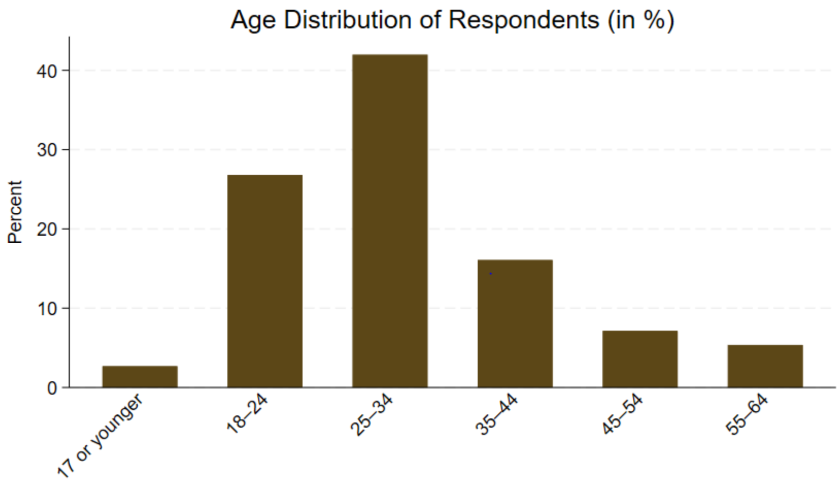

Figure 6 Age Distribution of Respondents

Almost 42% of respondents are between 25 and 34 years old and nearly 27% are in the 18 to 24 age group. The lowest proportion, at just under 3%, is 17 years and younger. The remaining participants are split between the other three groups, with the group aged between 35 and 44 being significantly larger than the other two. The demographic variables were divided into groups so that comparisons could be made more easily. The age of the respondents was divided into 3 groups. The groups 17 or younger and 18-24, the groups 25-34 and 35-44, and the groups 45-54 and 55-64 were combined. There were no participants in the 65 or older group.

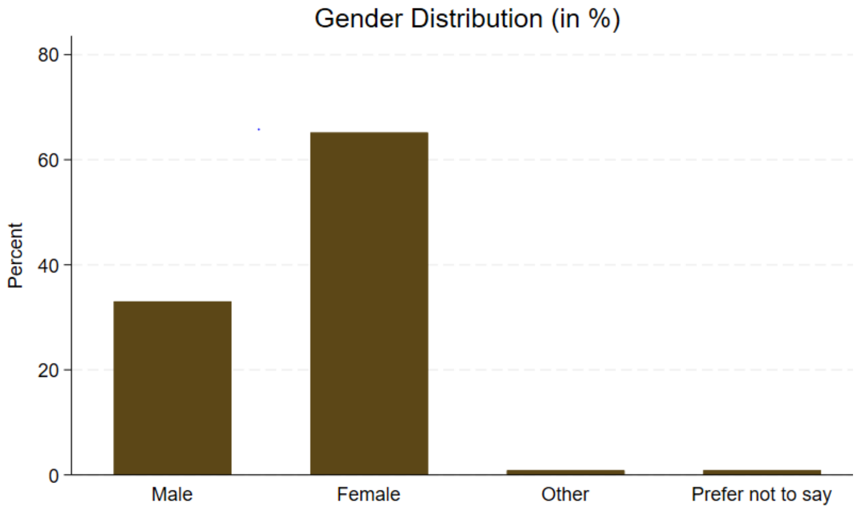

Figure 7 Gender Distribution

Female participants predominate in the sample, and the proportion is around 65%. 33% of the respondents were male and less than 1% each categorised themselves in the Other or Prefer not to say group. Gender was divided into two groups, namely female and male, as there was only one answer in each of the other two categories.

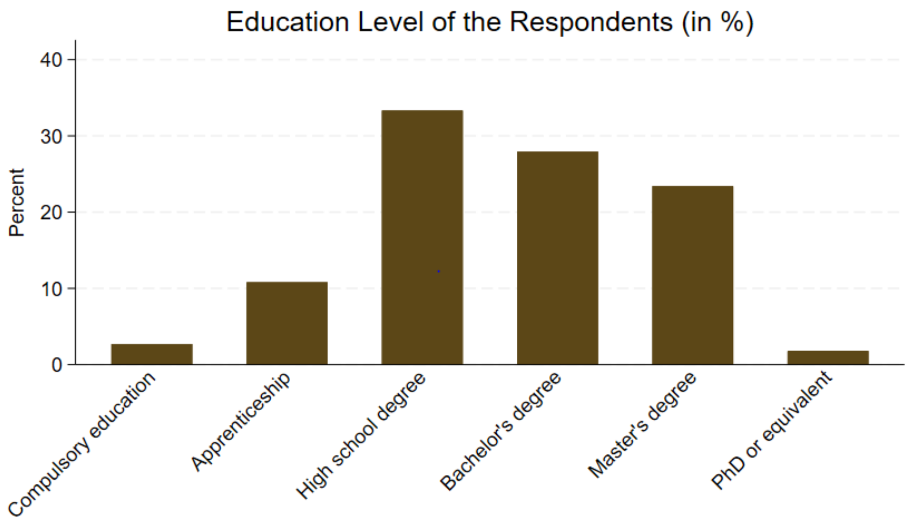

Figure 8 Education Level of Respondents

The majority of participants hold either a High School degree, a bachelor's degree, or a master's degree, each accounting for over 20% of the sample. Just over 10% have completed an apprenticeship, while slightly more than 1% hold only compulsory education or a PhD (or equivalent). For education, the categories compulsory education and apprenticeship, high school degree and bachelor's degree, and master's degree and PhD or equivalent were combined.

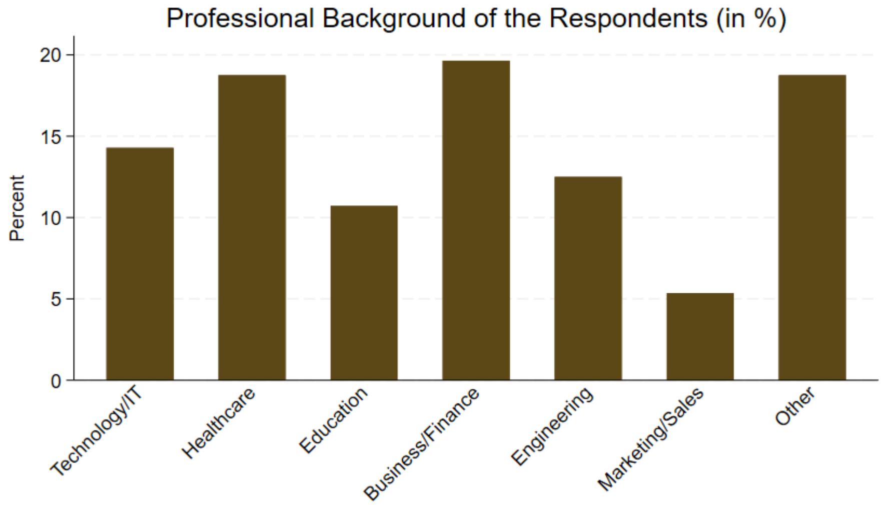

Figure 9 Professional Background of Respondents

The professional backgrounds of the survey participants are diverse. Technology/IT, Healthcare, Business/Finance, and Others each represent over 15% of respondents, with the largest share—almost 20%—coming from the Business and Finance sector. In contrast, just over 5% work in Marketing and Sales. The 'Other' category includes fields such as Law and Psychology. In the professional background category, Technology/IT and Engineering, Business/Finance and Marketing/Sales, and Healthcare and Education were combined.

The Experience with AI variable was measuring using a 5- point Likert scale, where 1 indicates very low or no experience with AI systems and 5 indicates very high experience.

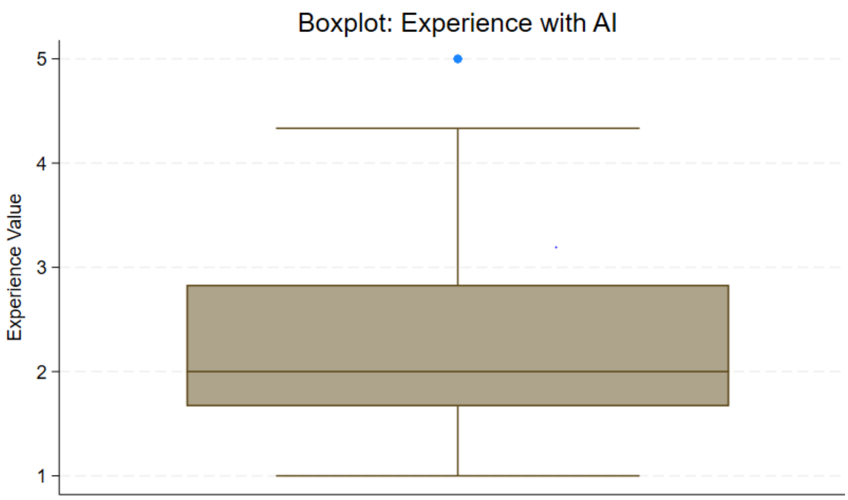

Figure 10 Experience with AI

The average Experience with AI is around 2.2 and is therefore rather low on a scale of 1 to 5.

Table 3 shows the variables, which are divided into the areas of *recruitment*, *selection*, and *training & development*.

Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Cronbach´s Alpha
Acceptance Recruitment	121	3.72	.72	1	5	0.75
Perceived Ease Recruitment	121	3.58	.72	1	5	0.81
Trust Recruitment	120	2.75	.68	1	4.4	0.72
Acceptance Selection	117	3.28	.86	1	5	0.85
Trust Selection	117	2.78	.74	1	4.2	0.77
Acceptance T&D	110	3.69	.82	1	5	0.87
Perceived Ease T&D	110	3.87	.88	1	5	0.90
Trust T&D	109	2.98	.74	1	4.4	0.80

Table 3 Descriptive Statistics for Survey Variables in Recruitment, Selection, and Training & Development

The number of observations is not always the same and ranges between 121 and 109. The number of observations for training & development is lower because not all participants completed the sections of the survey. All Cronbach's alpha values for the variables are above 0.7, indicating acceptable reliability, as shown in detail in the table.

In the further course of the analysis, some correlations were carried out to understand the relationships between the variables. There is a positive correlation between the three variables acceptance in recruitment, selection, and training & development. However, the correlations are only moderate, which indicates that acceptance may vary depending on the field of application.

Pairwise correlations

Variables	(1)	(2)	(3)
(1) Acceptance Recruitment	1.000		
(2) Acceptance Selection	0.493*	1.000	
	(0.000)		
(3) Acceptance T&D	0.444*	0.288*	1.000
	(0.000)	(0.002)	

**** p<0.01, ** p<0.05, * p<0.1*

Table 4 Correlations between acceptance variables across HRM areas

Correlations were carried out with the different variables in the various areas, as shown in Appendix C, D, and E. The correlations between the dependent and independent variables in the three areas are statistically significant, indicating meaningful relationships within the sample. Furthermore, the results show that trust and perceived ease of use are important factors influencing acceptance. Trust is particularly important in the selection sector and perceived ease of use is more important in the training & development sector. In recruitment, both play a relatively equal role. The exact results and further correlations with the various combinations of variables can be seen in the appendix C, D, and E.

To examine whether demographic and background factors influenced acceptance different T-tests and Anova group comparisons were carried out in each area. The exact tables can be seen in the appendix C, D, and E. In recruitment, no significant differences in acceptance were found according to education level, gender, experience with AI, background, and age. No significant differences were found in the selection category either. There are also no significant differences in the training & development category.

To test the hypotheses, regressions were carried out for each area to examine the effects of the independent and control variables on acceptance.

To test the Hypothesis 1 that higher trust in AI-supported recruitment tools is associated with higher acceptance of their use, a multiple linear regression was performed (see Table 9). The dependent variable was acceptance in recruitment, while the independent variable was trust in recruitment. Educational level, age group, experience with AI and gender were included as control variables. Dummy codes with reference categories were used for the control variables. This means that the effects of the individual groups must always be interpreted in comparison to the reference category. Robust standard errors are used to account for potential heteroscedasticity.

VARIABLES	Model 1
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.23
	(0.19)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	-0.02
	(0.21)
Age: 25-44 years (vs. ≤ 24)	-0.11
	(0.15)
Age: 45-64 years (vs. ≤ 24)	0.38*
	(0.22)
Experience AI	0.03
	(0.08)
Gender: Female (vs. Male)	0.17
	(0.12)
Trust Recruitment	0.48***
	(0.10)
Constant	2.40***
	(0.46)
Observations	108
R-squared	0.30

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Regression analysis with acceptance in recruitment as dependent variable, trust in recruitment as independent variable and control variables

The results show that the model is significant overall ($F(7, 100) = 5.86$, $p < .001$) and has an explained variance (R^2) of 30%. The independent variable shows a positive and statistically significant effect on the acceptance of AI in recruitment ($\beta = 0.48$, $p < .001$). This means that a higher level of trust in AI systems in recruitment is associated with a significantly higher level of acceptance for their use in the recruitment process.

With regard to the control variables, the coefficients for educational level (reference category: compulsory education/apprenticeship), age group (reference category: 17-24 years), experience with AI, and gender (reference category: male) are not statistically significant, as their p-values exceed the conventional significance thresholds. The only exception is the 45-64 age group, which shows a positive effect on acceptance ($\beta = 0.38$, $p < 0.1$), suggesting that older participants in this group are slightly more likely to accept AI in HRM than the younger reference group.

To test the requirements of the regression analysis, multicollinearity is examined using the variance inflation factor (VIF). All variables are well below the critical threshold value of 10, with an average VIF of 1.55.

The results provide empirical support for the hypothesis. The regression analysis shows that trust in AI-supported recruitment programs has a significant influence on the acceptance of their use, while other demographic and experiential factors play a negligible role.

In the first step, regressions for H2 were carried out with the variables created, but the multicollinearity was far too high for the model. For this reason, the regression was carried out again with centred variables. (model without the centred variables in the appendix)

Centred variables were used in the regression analysis because this method reduces multicollinearity, especially in the case of interactions, which makes the estimates more stable and precise. Centred variables also improve the numerical stability of the model and prevent bias due to extremely high or low values. Overall, centring leads to a more comprehensible and robust model, especially for complex interactions or variables of different scales (Cohen et al., 2003).

Before including the interaction term, a correlation between perceived ease of use and trust in AI in recruitment was calculated. The correlation was low ($r = 0.286$), suggesting that both variables can be included in the model simultaneously without fear of multicollinearity.

To test the Hypothesis 2 that the relationship between perceived ease in recruitment and acceptance in recruitment is moderated by trust in AI in recruitment, a multiple linear regression was performed. In addition to the interaction term (perceived ease of use x trust in recruitment), control variables are added to the model (see Table 10). Robust standard errors were used in the analysis.

VARIABLES	Model 1
Age: 25-44 years (vs. ≤ 24)	-0.15
	(0.13)
Age: 45-64 years (vs. ≤ 24)	0.29
	(0.20)
Gender: Female (vs. Male)	0.09
	(0.11)
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.29*
	(0.17)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	-0.05
	(0.19)
Background: Business (vs. Technology)	0.30**
	(0.14)
Background: Healthcare & Education (vs. Technology)	0.11
	(0.17)
Background: Other (vs. Technology)	0.02
	(0.16)
Experience AI	-0.05
	(0.07)
Perceived Ease of Use	0.33**
	(0.15)
Trust (Recruitment)	0.32***
	(0.09)
Moderator Trust (Recruitment)	-0.12
	(0.11)
Constant	3.93***
	(0.27)
Observations	108
R-squared	0.46

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Regression analysis with acceptance in recruitment as dependent variable, perceived ease of use in recruitment as independent variable, trust in recruitment as moderator and control variables

The model explains 45.8% of the variance in the acceptance of AI systems in the recruitment area ($R^2 = 0.4576$) and is significant overall ($F(12, 95) = 7.41$, $p < .001$). Perceived ease of use shows a positive effect on acceptance ($\beta = 0.327$, $p < .001$). Similarly, trust in AI systems remains a strong predictor ($\beta = 0.316$, $p < .001$). In contrast, the interaction term between perceived ease of use and trust is not significant ($\beta = - 0.116$, $p < .291$), which indicates that no moderating effect of trust on the relationship between perceived ease of use and acceptance in recruitment could be determined. Individual control variables also show effects. Participants with a professional background in business show a significantly higher acceptance of AI systems in recruitment than the reference group (technology), with a positive coefficient of $\beta = 0.304$ ($p = .028$). None of the other control variables show significant effects. The multicollinearity test does not reveal any critical values (all VIFs < 2.5; mean = 1.73).

The results support the assumption of a direct positive effect of the perceived ease of use of AI systems on their acceptance. However, there is no empirical evidence for a moderating influence of trust in AI on this relationship. The hypothesis that trust acts as a moderator of the effect of perceived ease of use is therefore not confirmed.

To test the Hypothesis 3, which states that trust in AI systems in selection tools is a significant predictor for the acceptance of AI-supported selection procedures, a multiple linear regression with robust standard errors was performed. The dependent variable was acceptance in selection and the independent variable was trust in selection. In addition, demographic control variables and experience with AI were considered (see Table 11). Robust standard errors were applied to account for potential heteroscedasticity.

VARIABLES	Model 1
Age: 25-44 years (vs. ≤ 24)	-0.17
	(0.16)
Age: 45-64 years (vs. ≤ 24)	-0.07
	(0.21)
Gender: Female (vs. Male)	0.07
	(0.13)
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.03
	(0.20)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	-0.25
	(0.21)
Background: Business (vs. Technology)	-0.08
	(0.18)
Background: Healthcare & Education (vs. Technology)	0.00
	(0.18)
Background: Other (vs. Technology)	-0.22
	(0.20)
Experience AI	0.04
	(0.07)
Trust (Selection)	0.76***
	(0.09)
Constant	1.28***
	(0.44)
Observations	109
R-squared	0.48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 Regression analysis with acceptance in selection as dependent variable, trust in selection as independent variable and control variables

The results, shown in Table 11, indicate that the model is highly significant overall ($F(10,98) = 13.12$, $p < .001$) and explains 47.9% of the variance in acceptance of AI selection tools ($R^2 = 0.479$, $p < 0.001$) and thus shows a solid model quality. As described in the hypothesis, trust in AI proves to be a highly significant predictor of the acceptance of AI in the selection context ($\beta = 0.759$, $p < 0.001$). As expected, the direction of the correlation is positive. The higher the trust in AI-supported selection procedures, the greater their acceptance among respondents. None of the control variables reached the significance level ($p > 0.05$). The multicollinearity test revealed no signs of critical correlations between the explanatory variables (mean VIF = 1.74).

The results support the hypothesis. Trust in AI-supported selection tools has a clear and statistically significant influence on the acceptance of AI in selection procedures.

To test Hypothesis 4, a multiple linear regression model was estimated to examine the influence of perceived ease of use and trust on acceptance in the training & development area. The dependent variable was acceptance in training & development, while the independent variables were perceived ease of use and trust in AI for training & development. Additional control variables were added to the model.

VARIABLES	Model 1
Gender: Female (vs. Male)	-0.08
	(0.17)
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.10
	(0.20)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	0.10
	(0.22)
Background: Business (vs. Technology)	0.15
	(0.18)
Background: Healthcare & Education (vs. Technology)	0.16
	(0.23)
Background: Other (vs. Technology)	0.07
	(0.20)
Perceived Ease T&D	0.50***
	(0.10)
Trust (T&D)	0.31**
	(0.13)
Constant	0.82
	(0.65)
Observations	106
R-squared	0.43

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Regression analysis with acceptance in T&D as dependent variable, perceived ease of use in T&D and trust as independent variables and control variables

The model quality can be classified as satisfactory with an R^2 of 43.3%. The overall model achieves statistical significance ($F(8, 97) = 6.59$, $p < 0.001$), which indicates an adequate explanation of variance by the included predictors. As hypothesized, the perceived ease of use of AI applications in training & development proves to be a highly significant predictor of acceptance ($\beta = 0.504$, $p < 0.001$). Trust in AI also shows a significant positive influence on acceptance ($\beta = 0.310$, $p = 0.016$). None of the control variables considered reached statistical significance (all $p > 0.40$), which suggests that gender-specific or education-related differences as well as professional backgrounds do not have any independent explanatory power in this model. An examination of potential multicollinearity did not reveal any conspicuous values (mean VIF = 1.77).

The results provide empirical support for Hypothesis 4, confirming that both perceived ease of use and trust contribute significantly to explaining the acceptance of AI tools in the area of training & development.

To test Hypothesis 5, a multiple regression model with centred variables and with an interaction term was estimated (see Table 13). The aim was to analyse whether trust in AI systems influences the relationship between perceived ease of use and acceptance in training & development. In addition, control variables were included in the model.

The correlation between perceived ease of use and trust is low to moderate ($r = 0.23$), showing that the variables are related but sufficiently independent to be included together in the regression model.

VARIABLES	Model 1
Age: 25-44 years (vs. ≤ 24)	0.11
	(0.13)
Age: 45-64 years (vs. ≤ 24)	-0.01
	(0.30)
Gender: Female (vs. Male)	-0.07
	(0.17)
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.12
	(0.21)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	0.06
	(0.23)
Background: Business (vs. Technology)	0.09
	(0.18)
Background: Healthcare & Education (vs. Technology)	0.16
	(0.24)
Background: Other (vs. Technology)	0.02
	(0.20)
Experience AI	- 0.04
	(0.08)
Perceived Ease T&D	0.47***
	(0.11)
Trust (T&D)	0.29**
	(0.14)
Moderator Trust (T&D)	-0.15**
	(0.07)
Constant	3.79***
	(0.36)
Observations	106
R-squared	0.45

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 Regression analysis with acceptance in T&D as dependent variable, perceived ease of use in T&D as independent variable, trust in T&D as moderator and control variables

The main effects of both central predictors are significant. Perceived ease of use has a strong positive influence on acceptance ($\beta = 0.47$; $p < 0.001$) and trust in AI also shows a significant positive main effect ($\beta = 0.29$; $p = 0.036$). Central to the hypothesis is the interaction effect between perceived ease of use and trust, which was statistically significant ($\beta = - 0.15$; $p = 0.039$). The negative coefficient suggests that the positive effect of perceived ease of use on acceptance diminishes slightly at higher levels of trust, indicating that trust partially moderates the importance of perceived ease of use. None of the control variables showed significant effects (all $p > 0.40$). There are also no signs of problems with multicollinearity (mean VIF = 1.73).

These results confirm the moderating role of trust in AI systems in the context of training & development and thus support the hypothesis. The effect of perceived ease of use on the acceptance of AI applications in the area of training & development is not independent but depends on the level of trust of the users.

New variables had to be created so that the regression for Hypotheses 6 could be carried out. The general acceptance of AI-supported systems in the HRM context is a variable for general trust. The general acceptance was formed from the variables of the individual areas, as was the general trust.

Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Cronbach´s Alpha
Acceptance Overall	121	3.56	.62	1	4.8	0.86
Trust Overall	121	2.83	.66	1	4.2	0.91

Table 10 Summary Variables (Overall)

To test the Hypothesis 6 that trust in AI systems has a significant influence on their general acceptance in the HRM context, a linear regression model was estimated (see Table 15). The model also included demographic control variables (age, gender, level of education, professional background) and experience with AI systems (experienceAI).

VARIABLES	Model 1
Age: 25-44 years (vs. ≤ 24)	-0.11
	(0.11)
Age: 45-64 years (vs. ≤ 24)	0.03
	(0.19)
Gender: Female (vs. Male)	0.06
	(0.11)
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.07
	(0.14)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	-0.04
	(0.15)
Background: Business (vs. Technology)	0.07
	(0.13)
Background: Healthcare & Education (vs. Technology)	-0.04
	(0.15)
Background: Other (vs. Technology)	-0.11
	(0.15)
Experience AI	0.03
	(0.05)
Trust Overall	0.59***
	(0.08)
Constant	1.89***
	(0.36)
Observations	109
R-squared	0.46

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11 Regression analysis with general acceptance of AI systems as dependent variable, general trust as independent variable and control variables

The regression model explains 46% of the variance in overall acceptance ($R^2 = 0.462$; $F(10, 98) = 6.67$; $p < 0.001$), which indicates a very good model quality. The central predictor trust shows a highly significant and positive effect on the overall acceptance of AI ($\beta = 0.59$; $p < 0.001$), demonstrating that higher trust in AI systems is associated with higher acceptance across HRM processes. All demographic control variables showed no significant effects (all $p > 0.30$). From a multicollinearity perspective, there are no concerns, with an average VIF of 1.75.

The results provide clear empirical evidence for the assumption that trust in AI systems is a central influencing factor for their overall acceptance in the HRM context and the hypothesis can therefore be supported.

Trust as Dependent Variable:

To analyse whether socio-demographic characteristics influence trust in AI systems, trust was treated as the dependent variable in separate regression models for each HRM area. Age, gender, level of education, professional background, and experience with AI were included as predictors.

In the area of recruiting, a linear regression model shows that none of the demographic variables (age, gender, education, professional background, experience with AI) has a significant influence on trust in AI systems (all $p > 0.10$). The model explains only 5.8 % of the variance in trust ($R^2 = 0.058$) and is not significant overall ($F(8, 99) = 0.62$; $p = 0.755$). Multicollinearity was unproblematic (average VIF < 2). Trust in AI in the area of recruitment cannot be explained by demographic characteristics (see the regression model in the appendix G).

A linear regression model shows that none of the demographic variables has a significant influence on trust in AI systems in the context of selection procedures (all $p > 0.10$). The explained variance is low ($R^2 = 0.069$), and the model is not significant overall ($p = 0.425$). Multicollinearity is not a problem (mean VIF = 1.85). Trust in AI in selection decisions is not explained by demographic characteristics (see the regression model in the appendix G).

The regression model in the area of training & development explains 12.4 % of the variance in trust in AI systems in the training & development context ($R^2 = 0.124$) and is borderline significant ($F(8, 97) = 1.78$; $p = 0.090$). Two demographic variables show significant effects. Age group 2 (26-35 years) shows significantly lower confidence compared to the reference group (18-25 years) ($\beta = -0.367$; $p = 0.037$). Professional background group 4 (no relation to HRM or technology) also shows significantly less confidence compared to the reference group (HRM background) ($\beta = -0.516$; $p = 0.020$). All other variables (gender, level of education, other age, and background groups) show no significant effects (all $p > 0.1$). Multicollinearity is unproblematic (mean VIF = 1.89). Certain age and professional background groups show less trust in AI in the area of training & development (see in the regression model in the appendix G).

The results indicate that, overall demographic characteristics have little influence on trust in AI systems. Only specific age and professional background groups show reduced trust in the training & development context.

To analyse whether socio- demographic characteristics influence overall trust in AI systems, a linear regression model was estimated with age group, gender, level of education and professional background as predictors (see Table 16).

VARIABLES	Model 1
Age: 25-44 years (vs. ≤ 24)	-0.21
	(0.15)
Age: 45-64 years (vs. ≤ 24)	-0.07
	(0.22)
Gender: Female (vs. Male)	0.09
	(0.18)
Educ: High School/ bachelor's degree (vs. Compulsory/Apprenticeship)	-0.19
	(0.17)
Educ: Master's degree/ PhD (vs. Compulsory/Apprenticeship)	-0.15
	(0.21)
Background: Business (vs. Technology)	0.17
	(0.18)
Background: Healthcare & Education (vs. Technology)	-0.18
	(0.22)
Background: Other (vs. Technology)	-0.34*
	(0.19)
Constant	3.17***
	(0.17)
Observations	109
R-squared	0.09

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12 Regression analysis with general trust as dependent variable

The linear regression model explains only 8.8 % of the variance in overall trust in AI systems in the HRM context ($R^2 = 0.088$; $F(8, 100) = 1.33$; $p = 0.235$), indicating that the included predictors do not significantly explain trust. None of the demographic variables reached significant influence (all $p > 0.07$), whereby background group other jobs (no relation to HRM or technology) shows a marginal lower level of trust compared to the reference group (HRM background) ($\beta = -0.342$; $p = 0.074$). Multicollinearity is insignificant (mean VIF = 1.85).

Overall, the results suggest that sociodemographic characteristics have little to no influence on overall trust in AI systems. Trust in AI appears to be independent of age, gender, education, and most professional backgrounds, with only marginal effects for participants unrelated to HRM and technology.

4.2 Discussion

The results of this study offer substantial information regarding the trust and acceptance of AI systems in various fields of application in HRM. The mean values of the measured variables in all three application areas (recruitment, selection, training & development) range between 3 and 4 on a five-point scale. This indicates a generally positive but not unreservedly high level of acceptance. Although AI systems offer potential in the HRM sector, this moderate rating suggests that people do not fully perceive them as trustworthy and helpful. This is consistent with previous research findings suggesting that employees often have a conditional attitude toward AI, especially when systems influence personal outcomes (Raisch & Krakowski, 2021). Although AI has recognized potential for improving efficiency and objectivity, employees do not yet fully perceive these systems as trustworthy or helpful, highlighting the ambivalence often observed in relation to algorithmic decision-making processes.

The regression analyses provide empirical evidence for the role of trust and perceived ease of use as key influencing factors in HRM's acceptance of AI systems. However, there are sector-specific differences in strength and effect. All tested hypotheses in which trust acted as an explanatory variable (H3, H4, H5, H6) were fully or partially confirmed.

Trust was a significant and positive predictor of acceptance in several models (including H1, H3, H4, and H6), thus confirming previous work that emphasizes the importance of trust in dealing with algorithmic systems (Glikson & Woodley, 2020; Siau & Wang, 2018). This study underlines the assumption that employees base their acceptance of AI-supported systems largely on the extent to which they trust these technologies. It is assumed that trust reduces uncertainty and perceived risks when interacting with AI, especially in contexts involving high personal or professional risks (Dietvorst et al., 2015; Mayer et al., 1995).

Perceived ease of use also showed a significant positive effect on acceptance in various contexts, which is in line with the Technology Acceptance Model (TAM) according to Davis (1989) and its extensions (Venkatesh & Davis, 2000; Venkatesh et al., 2003). These findings support the assumption that cognitive assessments of perceived ease of use remain crucial, especially in contexts where employees interact directly with AI systems for learning and development purposes (Holden & Karsh, 2010).

Descriptive statistics show differences in the level of trust between the areas. The average trust value was lowest in the area of recruiting, slightly higher in the area of personnel selection, and highest in the area of training and development. Although these differences appear to be small, these patterns are meaningful in light of contextual factors. Recruitment is often perceived as a routine and procedural process that requires less emotional trust, whereas selection decisions have significant personal consequences and require a higher level of perceived trustworthiness (Langer et al., 2018; Lee & Jin, 2019). This phenomenon is reflected in the higher regression coefficient for trust in the selection domain, showing that perceived risks reinforce the role of trust in shaping acceptance (Glikson & Woodley, 2010).

The interaction effects of trust in AI on the relationship between perceived ease of use and acceptance (H2 & H5) showed differentiated results. The interaction effect did not remain significant in recruiting, which indicates a rather parallel effect of the two variables. In training & development, there was also a significant negative interaction effect between trust and perceived ease of use (H5), which indicates that high trust relativizes the influence of perceived ease of use on acceptance. This pattern aligns with theoretical frameworks positions a complementary relationship between affective (trust) and cognitive (ease of use) antecedents of technology adoption (Gefen et al., 2003). When trust is high, employees rely less on perceived ease of use to evaluate the system, whereas when trust is low, perceived ease of use becomes a decisive factor for acceptance (Lankton et al., 2015). In training & development, trust is shown to be important, but not as an isolated predictor, as trust and perceived ease of use have a reciprocal effect in this area. This could mean that users who have strong trust in AI systems are less dependent on their intuitive usability to accept them.

The analysis of overall acceptance across the domains (H6) once again confirmed the prominent role of trust as a central predictor. These analyses made it clear that trust explains a considerable part of the variance in the overall acceptance of AI in HRM. These differences in the results suggest that the requirements for AI systems and the expectations of users are context dependent. Reliability and fairness, and therefore trust, are particularly important in more heavily evaluated processes, such as personnel selection, while practical handling and perceived ease of use are also key in the training and development sector.

The analyses show that demographic characteristics had only a very limited influence on trust in AI-supported HRM systems. In the areas of recruitment and selection, none of the variables tested—age, gender, educational level, professional background, or AI experience—had a significant impact on trust. In the area of training and development, however, two significant effects were observed: participants in the 26-35 age group reported lower trust, and respondents without an HRM or technology-related professional background showed significantly lower trust. These findings could indicate target group-specific needs in the introduction of AI (Zarouali et al., 2021). This result is confirmed by existing literature, which shows that experiences and system-related cues have a greater influence on trust formation than personal characteristics (Lee & See, 2004; McKnight et al., 2011). These results could indicate specific experiences or reservations in these groups but require further investigation. Apart from these two results, no other demographic variable achieved significant importance in any of the three areas of application.

Analyses of overall trust in all areas of HRM confirmed these patterns, with demographic characteristics explaining only a tiny portion of the variance. Taken together, these results show that trust in AI systems is largely independent of sociodemographic characteristics and is instead more strongly influenced by cognitive and experiential factors such as perceived ease of use.

Taken together, these results show that trust and perceived ease of use are key predictors of AI acceptance in HRM, but their relative influence depends on the context, as trust is more important in high-risk areas such as selection, while perceived ease of use becomes more important in interactive areas such as training and development. The complementary interaction between trust and perceived ease of use further underscores the complicated relationship among affective and cognitive factors in the acceptance of AI systems.

Theoretical Implications

The results support the central assumptions of the Technology Acceptance Model (Davis, 1989), as well as its extensions (Venkatesh et al., 2003), by identifying trust and perceived ease of use as key factors for acceptance. Both trust and perceived ease of use proved to be robust predictors of the acceptance of AI-supported HRM systems in various areas of application. This is consistent with the TAM framework, which emphasizes the cognitive evaluation of perceived ease of use and extends it by showing that affective constructs such as trust play an equally central role in acceptance when technologies involve algorithmic decision-making.

At the same time, these results refine and extend the models by pointing to area- specific differences in the strength of predictors, demonstrating that the relative importance of these predictors is not uniform but context dependent. In the selection area, people perceive AI systems as highly risky to career opportunities and fairness, making trust particularly crucial. This conclusion is consistent with Lee and See (2004), who stated that the calibration of trust is strongly influenced by the perceived risks associated with automation, and with Pavlou (2003), who emphasized the role of trust in situations of uncertainty and potential personal loss. Conversely, in the area of training and development, perceived ease of use had a stronger influence, probably because employees interact directly and repeatedly with AI-based learning systems. This underscores that the predictive power of TAM constructs can vary depending on task characteristics and perceived risks, reflecting the call for a more contextualized understanding (Bagozzi, 2007; Venkatesh et al., 2012). These results emphasize the value of a contextualized perspective on TAM and show that domain-specific characteristics of HRM processes moderate the strength of established predictors.

Furthermore, the analysis of the interactions between trust and perceived ease of use provides a differentiated perspective on their interplay. Although the results were not consistent across all areas, they offer helpful information about the interplay between affective and cognitive mechanisms of technology acceptance. In the area of training and development, for example, a high level of trust appeared to mitigate the role of perceived ease of use, suggesting a complementary relationship between affective and cognitive precursors of technology acceptance (Gefen et al., 2003; Lankton et al., 2015). Although these interactions are complex and not always straightforward to interpret, they are nevertheless consistent with theoretical work suggesting that trust can function as both a direct predictor and a moderator in adoption models (McKnight et al., 2011). By examining these dynamics, the study contributes to the ongoing debate about whether trust should be conceptualized as an independent determinant, a boundary condition, or both (Benbasat & Wang, 2005).

Another theoretical contribution lies in the minimal role of demographic factors in trust in AI systems. In recruitment and personnel selection, none of the demographic variables tested (age, gender, professional background, education level, AI experience) had a significant impact. Only in the area of training and development were slight deviations found, with participants aged 26 to 35 and those without an HRM or technology background expressing lower levels of trust. Overall, however, sociodemographic characteristics explained only a small portion of the variance in trust. These results are consistent with the study by Hoff and

Bashir (2014), which emphasized that system-related factors (transparency, reliability, performance) play a greater role in building trust than user characteristics, as well as McKnight et al. (2011), who also found that experiential and cognitive factors outweigh demographic factors. Theoretically, this supports the idea that the acceptance of AI-supported HRM systems depends less on who the user is and more on how the system is perceived, further refining the TAM by locating acceptance in the realm of perception and experience rather than sociodemographic predispositions.

Together, these findings theoretically demonstrate that traditional technology acceptance models alone cannot explain the adoption of AI in HRM. Instead, we require a more nuanced perspective that considers contextual factors and the interaction between affective and cognitive mechanisms. This underscores the value of integrating trust theories (Hoff & Bashir, 2014; Mayer et al., 1995) into established acceptance frameworks, thereby promoting a more comprehensive understanding of AI adoption in organizational contexts.

Practical Implications

For the successful implementation of AI systems in HRM, companies should take targeted measures to promote trust and perceived ease of use. An important first step is transparency and explainability, because employees are more likely to trust AI systems if they understand how decisions are made, if the logic of the algorithms is accessible, and if the limitations of the systems are openly communicated (Wirtz et al., 2019). Providing clear information about the purpose, data sources, and limitations of AI use helps reduce uncertainty and strengthen the perception of fairness.

In addition, traceability and accountability structures should be integrated into HRM processes. This includes providing applicants and employees with channels for feedback, giving them the opportunity to challenge AI-supported decisions, and reassuring them that ultimate responsibility lies with human decision-makers (Khan & Sheoran, 2025). Such mechanisms promote balanced trust by ensuring that AI systems are not perceived as opaque authorities but as tools embedded in a broader socio-technical system.

Another important point is user-centred design. The results of this study show that perceived ease of use is particularly important in interactive areas such as training and development. Therefore, AI applications in HRM should have simple, intuitive user interfaces and be tailored to the actual processes of applicants and employees. This not only improves perceived ease of use (Davis, 1989) but also signals that the technology is tailored to the needs of employees and not imposed from above.

In addition, education and training initiatives are essential to promote acceptance. Previous research shows that user competence and familiarity with the technology directly contribute to a positive attitude and trust (Venkatesh & Davis, 2000). Companies should therefore offer tailored training programs ranging from technical introductory sessions to workshops covering the ethical and legal aspects of AI. Involving employees in pilot projects at an early stage can also help reduce resistance and build trust by promoting a sense of participation and control (Meijerink et al., 2021).

Finally, the implementation process should follow a socio-technical approach. Trust is not created solely by technical features, but by the interaction of systems, organizational culture, and values. A holistic implementation strategy should therefore integrate ethical guidelines, align with existing organizational values, and ensure that applicants and employees perceive AI as a support rather than a replacement (Bostrom & Yudkowsky, 2014; Hoff & Bashir, 2014). We can maintain trust in all areas of HRM by embedding AI systems in an organizational culture that values fairness, accountability, and participation.

Taken together, these implications suggest that organizations should not only focus on the technical robustness of AI systems but also actively manage the socio-cognitive processes of trust building. Through transparency, accountability, perceived ease of use, education, and cultural alignment, the introduction of AI in HRM can be implemented in a way that promotes both trust and acceptance.

5. Conclusion and Directions for Future Research

The aim of this study was to examine the role of trust in the acceptance of AI in HRM, focusing on three key areas of application: recruiting, selection, and training and development. Based on the Technology Acceptance Model and its extensions, the study showed that trust not only acts as a direct predictor but also as a moderating factor in certain contexts. These findings enhance existing acceptance models and offer distinct insights into how employees and applicants perceive AI systems in HRM.

The results show that trust is a decisive factor for the acceptance of AI in all areas of HRM, although its significance varies depending on the context. In recruiting, trust is a significant predictor of acceptance ($\beta = 0.48$, $p < 0.001$; $R^2 = 0.30$), while perceived ease of use also has a positive effect ($\beta = 0.33$, $p < 0.01$). The interaction between trust and perceived ease of use was not significant ($\beta = -0.12$, $p = 0.291$), suggesting that both factors contribute independently to acceptance.

To improve legibility, replace with: In the area of selection, trust is the dominant predictor ($\beta = 0.76$, $p < 0.001$; $R^2 = 0.48$), while demographic control variables such as age, gender, or education are not significant. This underscores the increased sensitivity of selection processes in which fairness, objectivity, and ethical considerations are of paramount importance.

A different pattern was observed in training and development. Perceived ease of use is a strong predictor of acceptance ($\beta = 0.50$, $p < 0.001$), and trust has a significant positive effect ($\beta = 0.31$, $p = 0.016$). Importantly, trust has a moderating effect in the area of training and development ($\beta = -0.15$, $p = 0.039$), suggesting that the positive effect of perceived ease of use on acceptance decreases slightly at higher levels of trust. This indicates that trust partially compensates for the influence of perceived ease of use in this context.

The analysis of general acceptance in the various areas of HRM once again confirms the central role of trust. General trust explains 46% of the variance in general acceptance ($\beta = 0.59$, $p < 0.001$), while demographic variables such as age, gender, education, or professional background have only a minimal influence. Only participants with no experience in HRM or technology showed slightly lower trust ($\beta = -0.34$, $p = 0.074$). In the individual areas of recruiting and selection, demographic variables had no significant impact, while in training & development, certain age groups (26-35 years; $\beta = -0.37$, $p = 0.037$) and professional backgrounds (no connection to HRM/technology; ($\beta = -0.52$, $p = 0.020$) showed slightly lower trust.

Theoretically, this study expands TAM by integrating trust as both a direct and moderating factor. While classic TAM models focus primarily on perceived usefulness and perceived ease of use, the results show that trust—defined as the willingness to rely on AI-based decisions—is indispensable in the HRM context. In sensitive areas such as selection, where fairness and ethical responsibility are crucial, trust is the decisive factor for acceptance.

Furthermore, the study indicates that acceptance cannot be explained by technical characteristics alone. Rather, it arises from the interplay of psychological, ethical, and organizational factors. This opens up opportunities for integrative models that combine insights from information systems research, organizational psychology, and trust research.

The results of this study provide clear guidelines for companies wishing to implement AI systems in HRM. Trust is a key factor and should be consciously promoted through transparent communication about how AI systems work, how data is used, and how decisions are made. Employees and applicants should be actively involved in the implementation process, for example through training programs, feedback mechanisms, or participatory design approaches. Ethical considerations, fairness, and data protection must be integrated into AI strategies, as these dimensions have a significant impact on user trust and acceptance. In addition, different areas of HRM require tailored approaches. In recruiting, both trust and perceived ease of use are decisive for acceptance, while in training and development, intuitive interfaces and accessibility are particularly important.

Limitations

While this study offers valuable insights into the role of trust in the acceptance of AI systems in HRM, it is important to acknowledge its limitations.

The first set of limitations concerns the methodology. The number of valid cases per regression ranged from 109 to 121, which is at the lower threshold of what is generally considered sufficient for multiple regression analysis. Small sample sizes increase the risk of unstable parameter estimates, low statistical significance, and biased effect sizes (Green, 1991; Maxwell et al., 2008). These concerns are particularly relevant for analyses of moderating effects and subgroup comparisons, where the requirements for statistical significance are higher. Furthermore, the cross-sectional design prevents causal conclusions. Cross-sectional surveys can only capture correlations between variables but cannot determine temporal sequences or underlying causal mechanisms (Rindfleisch et al., 2008).

A second set of limitations concerns the composition of the sample. The sample was recruited via social media and personal contacts, which corresponds to a convenience sample. This method can lead to systematic biases, such as an overrepresentation of younger, better educated, and technologically interested respondents (Bethlehem, 2010). In fact, 42% of respondents in the study were between 25 and 34 years old and 65% identified as female, while older workers and those with lower levels of education were underrepresented. The unequal gender distribution may also have influenced the results, as previous research suggests that men and women may differ in their attitudes and acceptance behaviour toward technology (Venkatesh & Morris, 2000). As a result, the female perspective may heavily influence the results, limiting their generalizability to a more gender-balanced workforce. Such demographic imbalances limit the generalizability of the results to the broader working population (Fowler, 2014). Furthermore, data collection was limited to the German-speaking context, which restricts external validity. Cultural and organizational factors are known to influence perceptions of technology and trust, so the results may not be transferable to other national or organizational contexts (Hofstede, 2001).

Finally, the survey design also has limitations. The data was collected using a standardized online survey based exclusively on self-reported information. Although this method is efficient and well established in TAM and trust research (Gefen et al., 2003, McKnight et al., 2002), it also carries potential biases. First, asking participants to respond to hypothetical scenarios—imagining themselves as applicants or new employees—may limit ecological validity, as the attitudes reported do not necessarily predict actual behavior in corporate practice. Second, using a single data source for independent and dependent variables increases the risk of common method bias (Podsakoff et al., 2003). Third, the use of 5-point Likert scales, although widely used, has been shown to limit the sensitivity of the scale and comparability across different contexts (Joshi, et al., 2015). Finally, although validated measurement instruments were used (Choung et al., 2022; Davis, 1989; Jian et al., 2000), the items were adapted to the HRM and AI context. Such adaptations may compromise construct validity and reliability until they have been empirically tested in this specific environment.

In summary, the limitations of this study can be divided into three categories, namely methodological limitations relating to sample size and cross-sectional design, problems with the composition of the sample that limit generalizability, and challenges with the survey design, such as reliance on self-reported information, hypothetical scenarios, and measurement adjustments. These limitations provide starting points for future research.

Future Research

Based on the limitations discussed, several approaches for future research can be identified. First, longitudinal studies are needed to capture changes in trust and acceptance of AI systems over time. Cross-sectional data only provide statistical insights, whereas longitudinal studies would allow researchers to examine the dynamics of how trust develops, stabilizes, or declines when continuously confronted with AI in HRM (Venkatesh et al., 2012). This would also allow for stronger causal conclusions by establishing a temporal sequence.

Second, future studies should use experimental or quasi-experimental designs to examine the causal mechanisms underlying trust and acceptance. Controlled experiments, for example, can break down the effects of specific system characteristics (e.g., transparency, accuracy, fairness) on trust and behavioral intentions (Araujo et al., 2020). Such designs can complement survey-based research by overcoming problems of common method bias and limitations of self-reporting.

Third, additional psychological factors should be integrated into models of AI acceptance in HRM. Previous research highlights the relevance of constructs such as technology anxiety, perceived control, and self-efficacy, which significantly influence behaviour when technologies are introduced (Parasuraman & Colby, 2015; Venkatesh et al., 2003). Future research could investigate whether these factors interact with trust in shaping acceptance and whether they differ between different employee groups (e.g., by age, gender, or technology experience). In particular, the gender imbalance observed in the present sample suggests that future studies should consider potential gender differences in technology adoption. Previous work has shown that gender can influence perceptions of usefulness and ease of use (Venkatesh & Morris, 2000), which may also affect how trust influences the adoption of AI in human resource management.

Fourth, the role of technical and organizational characteristics deserves greater attention. For example, fairness, accountability, and transparency of AI systems have been identified as key elements that influence trustworthiness (Doshi-Velez & Kim, 2017; Mittelstadt et al., 2019). Examining these factors as mediating mechanisms could shed light on how trust is formed.

Similarly, organizational practices such as communication, training, and participation in AI implementation processes can strengthen or weaken employee acceptance (Bondarouk & Brewster, 2016).

Finally, comparative research across cultural and organizational contexts is crucial for improving generalizability. It is well known that cultural dimensions such as power distance or uncertainty avoidance influence perception (Hofstede, 2001; Tarhini et al., 2015). Investigating the acceptance of AI in HRM across different industries and countries could therefore reveal context-specific patterns and offer clues about the boundary conditions of existing models. The use of mixed methods approaches combining surveys with interviews, behavioural experiments, and usage data would further enrich understanding and enable triangulation.

Overall, future research should aim to move beyond static, self-report-based, single-context designs and toward longitudinal, experimental, and cross-cultural approaches. By integrating psychological, technical, and organizational dimensions, researchers can develop a more comprehensive and nuanced view of how trust in AI systems influences their acceptance in HRM.

In summary, this study indicates that trust is the most important factor for the acceptance of AI in HRM, while perceived ease of use remains important but depends on the context. The findings are of both theoretical and practical significance: they contribute to the further development of technology acceptance models and provide actionable guidelines for the responsible implementation of AI systems. A transparent, ethically grounded approach to AI, combined with organizational measures to promote trust, will determine whether AI is perceived as a reliable partner or a source of scepticism and resistance. By placing trust at the centre of AI implementation, companies can harness the full potential of these technologies to improve efficiency, fairness, inclusion, and employee engagement in HRM.

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7. Appendix

Appendix A: Survey

Dear participant,
my name is Anna Flöcklmüller and I am a Master´s student at the University of Vienna. As a part of my Master´s Thesis, I developed this online survey, which aims to gain insights into how acceptance of artificial intelligence influences user behaviour.
When answering the questions, imagine you are looking for a job and using various AI-powered tools and systems. These AI technologies support you throughout the entire process – from job searching and application to onboarding and further training in your new role.
Please answer the following questions from your perspective as an applicant or new employee.
The survey is divided into three sections: The first part focuses on AI recruitment tools, the second part examines AI selection tools and the third part explores the role of AI in training & development.
In each section of the survey, you will be asked to rate your agreement with several statements on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).
Please keep in mind that your answers will be kept anonymous and the survey will take 7-10 minutes to complete.
Thank you very much for your participation and time!

"AI recruitment tools are technologies used by HR departments that you might encounter during your job search and application process. These include job recommendation systems (e.g., personalized job suggestions on LinkedIn), AI-powered job boards, chatbots that answer your application-related questions, and resume optimization tools that help tailor your resume to specific job requirements."

Using AI-based tools in recruitment systems would improve my job application process.

AI-based tools in recruitment systems would enable me to accomplish job application tasks more quickly.

AI-based tools in recruitment systems would support me with job search activities.

Using AI-based tools during my job search would reduce the time I spend on unproductive activities.

As a job applicant, I would find it easy to use AI-based tools for job searching.

I would find it easy to navigate AI-powered job application systems.

My interaction with AI-powered chatbots and interfaces would be clear and understandable.

It would be easy for me to become proficient at using AI-driven job search and application platforms.

I trust that my personal data is protected when AI-based tools are used in the recruitment process.

I trust that companies providing AI systems for recruitment purposes comply with ethical and legal standards.

I can trust AI systems used by recruiters in the job posting and application process.

I am confident in the decisions made by AI systems used in identifying and attracting potential job candidates.

I am suspicious of the intent or output of AI systems used by recruiters in job posting and candidate sourcing processes.

"AI selection tools are technologies used by employers to evaluate job applicants during the hiring process. These include AI-driven resume screening, video interview platforms, skill assessments, and predictive analytics. As a job seeker, you may encounter these tools when submitting applications, completing online assessments, or participating in video interviews."

I believe AI selection tools used by employers would effectively address my need to find job opportunities matching my skills and qualifications.

I believe employers' use of AI selection tools would save me time during the job application process.

I believe employers' use of AI selection tools would improve the quality of feedback I receive during the job application process.

I believe employers' use of AI selection tools would enhance my overall experience in the job application process.

I trust that my personal data is protected when recruiters use AI systems in the candidate selection process.

I trust that companies providing AI systems for candidate selection purposes comply with ethical and legal standards.

I can trust AI systems used by recruiters when evaluating my application and qualifications during the candidate selection process.

I am confident in the decisions made by AI systems when recruiters use them to evaluate my application during the candidate selection process.

I am suspicious of the intent or output of AI systems used by recruiters to evaluate my application during the candidate selection process.

"HR departments use AI-powered training & development tools such as personalized learning platforms, automated content creation systems, interactive simulations, and AI-driven progress tracking and feedback systems."

Using AI systems would enhance my performance in training & development.

AI systems would enable me to complete training & development tasks more efficiently.

AI systems would enhance my training & development activities.

Learning to use AI systems for training & development would be easy for me.

I would find it easy to navigate and interact with AI-based platforms for training & development.

It would be easy for me to become proficient at using AI technologies for training & development activities.

I trust that my personal data is protected when AI systems are used in my training & development activities.

I trust that companies providing AI systems for training & development purposes comply with ethical and legal standards.

I can trust AI systems used in my training & development activities.

I am confident in the decisions made by AI systems used in planning and implementing my training & development activities.

I am suspicious of the intent or output of AI systems used in my training & development activities.

Demographic Information

What is your age?

17 or younger

18 – 24

25 – 34

35 – 44

45 – 54

55 – 64

65 or older

What is your gender?

Male

Female

Other

Prefer not to say

What is the highest degree or level of education you have completed?

Compulsory education

Apprenticeship

High school degree

Bachelor´s degree or equivalent

Master´s degree or equivalent

PhD or equivalent

What is your professional background?

Technology/IT
Healthcare

Education

Business/Finance

Engineering

Marketing/Sales

Other

Experience in AI Systems

How would you rate your current knowledge and experience with AI systems in recruitment processes?

How would you rate your current knowledge and experience with AI systems in selection processes?

How would you rate your current knowledge and experience with AI systems in training and development processes?

Appendix B: Experience with AI

Experience with AI has little influence on the acceptance of the various HRM processes. As none of the correlations are significant, this indicates that experience with AI in this sample does not have a strong or consistent correlation with acceptance in the various areas.

Pairwise correlations with Experience

Variables	(1)	(2)	(3)	(4)
(1) Experience AI	1.000			
(2) Acceptance Recruitment	0.053	1.000		
	(0.582)			
(3) Acceptance Selection	-0.003	0.493*	1.000	
	(0.973)	(0.000)		
(4) Acceptance T&D	0.071	0.444*	0.288*	1.000
	(0.462)	(0.000)	(0.002)	

**** p<0.01, ** p<0.05, * p<0.1*

Appendix C: Section Recruitment

Correlation in the recruitment area

Pairwise correlations in Recruitment

Variables	(1)	(2)	(3)
(1) Acceptance Recruitment	1.000		
(2) Perceived Ease Recruitment	0.454*	1.000	
	(0.000)		
(3) Trust Recruitment	0.491*	0.286*	1.000
	(0.000)	(0.002)	

**** p<0.01, ** p<0.05, * p<0.1*

Correlation with the variables from the recruitment sector and the p-values

```
. pwcorr acceptance_recruitment PE_recruitment trust_ethical_recruitment age_group educ_group gender_bin background_group experienceAI, sig

             | accept~t PE_rec~t trust_~t age_gr~p educ_g~p gender~n backgr~p
-------------+---------------------------------------------------------------
acceptance~t |   1.0000 
             |
             |
PE_recruit~t |   0.4538   1.0000 
             |   0.0000
             |
trust_ethi~t |   0.4909   0.2857   1.0000 
             |   0.0000   0.0016
             |
   age_group |   0.0851  -0.0004  -0.0174   1.0000 
             |   0.3724   0.9967   0.8564
             |
  educ_group |  -0.0224  -0.0842  -0.0751   0.1931   1.0000 
             |   0.8157   0.3793   0.4354   0.0423
             |
  gender_bin |   0.0882   0.0445   0.0249  -0.1555  -0.1172   1.0000 
             |   0.3594   0.6444   0.7972   0.1049   0.2247
             |
background~p |  -0.1013  -0.2061  -0.0861  -0.2179  -0.1569   0.5430   1.0000 
             |   0.2879   0.0292   0.3687   0.0210   0.1000   0.0000
             |
experienceAI |   0.0526   0.1559  -0.0569  -0.0754   0.0381  -0.0451  -0.0527 
             |   0.5819   0.1008   0.5528   0.4296   0.6916   0.6397   0.5812
             |

             | experi~I
-------------+---------
```

Correlation with experience in AI and recruitment variables and the p- values

```
. pwcorr experienceAI acceptance_recruitment PE_recruitment trust_ethical_recruitment, sig
```

	experi~I	accept~t	PE_rec~t	trust_~t
experienceAI	1.0000			
acceptance~t	0.0526	1.0000		
	0.5819			
PE_recruit~t	0.1559	0.4538	1.0000	
	0.1008	0.0000		
trust_ethi~t	-0.0569	0.4909	0.2857	1.0000
	0.5528	0.0000	0.0016	

T- test with acceptance in recruitment and gender (no significant difference)

```
. ttest acceptance_recruitment, by(gender_bin)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	37	3.655405	.126808	.771343	3.398227	3.912584
1	73	3.78653	.0785167	.6708472	3.630009	3.94305
Combined	110	3.742424	.0672613	.7054421	3.609115	3.875734
diff		-.1311243	.1424623		-.4135094	.1512608

```
    diff = mean(0) - mean(1)                                      t =  -0.9204
H0: diff = 0                                     Degrees of freedom =      108

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.1797         Pr(|T| > |t|) = 0.3594          Pr(T > t) = 0.8203

.
```

Regression for H1

```
. reg acceptance_recruitment  i.educ_group i.age_group c.experienceAI trust_ethical_recruitment, robust
```

Linear regression

Number of obs	=	110
F(6, 103)	=	7.09
Prob > F	=	0.0000
R-squared	=	0.3251
Root MSE	=	.62545

acceptance_recruitment	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
educ_group						
2	-.2234359	.1838566	-1.22	0.227	-.5880721	.1412003
3	-.0089515	.2066103	-0.04	0.966	-.4187143	.4008113
age_group						
2	-.1688517	.1405935	-1.20	0.233	-.4476858	.1099824
3	.3153856	.2223029	1.42	0.159	-.1254998	.7562709
experienceAI	.0460028	.0696041	0.66	0.510	-.0920404	.184046
trust_ethical_recruitment	.523666	.1038049	5.04	0.000	.3177936	.7295385
_cons	2.376272	.4316397	5.51	0.000	1.520217	3.232328

Regression for H2

```
. reg acceptance_recruitment i.age_group i.gender_bin i.educ_group i.background_group c.experienceAI c.PE_recruitment##c.trust_ethical_recruitment, robust
```

Linear regression

Number of obs	=	108
F(12, 95)	=	7.41
Prob > F	=	0.0000
R-squared	=	0.4576
Root MSE	=	.55586

acceptance_recruitment	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
age_group						
2	-.1489625	.1295644	-1.15	0.253	-.4061803	.1082553
3	.2900863	.1988904	1.46	0.148	-.1047611	.6849337
1.gender_bin	.093494	.1144444	0.82	0.416	-.133707	.3206949
educ_group						
2	-.2891016	.1688473	-1.71	0.090	-.6243058	.0461027
3	-.0530278	.1883597	-0.28	0.779	-.4269691	.3209134
background_group						
2	.3035453	.1363961	2.23	0.028	.0327647	.5743259
3	.1073005	.1650299	0.65	0.517	-.2203253	.4349264
4	.0192131	.1588025	0.12	0.904	-.2960497	.3344759
experienceAI	-.0517918	.070266	-0.74	0.463	-.1912875	.0877038
PE_recruitment	.6463753	.2418875	2.67	0.009	.1661679	1.126583
trust_ethical_recruitment	.731015	.4169466	1.75	0.083	-.0967286	1.558759
c.PE_recruitment#c.trust_ethical_recruitment	-.1161754	.1093366	-1.06	0.291	-.3332359	.1008852
_cons	.7553768	.8963425	0.84	0.401	-1.024088	2.534842

Appendix D: Section Selection

Correlation in the selection area

Pairwise correlations in Selection

Variables	(1)	(2)
(1) Acceptance Selection	1.000	
(2) Trust Selection	0.689* (0.000)	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Correlation with acceptance in selection, trust in selection and experience in AI

```
. pwcorr acceptance_selection trust_ethical_selection experienceAI, sig

             | accept~n trust_~n experi~I
-------------+---------------------------
acceptance~n |   1.0000
             |
             |
trust_ethi~n |   0.6891   1.0000
             |   0.0000
             |
experienceAI |  -0.0032  -0.0323   1.0000
             |   0.9734   0.7350
             |
```

Correlation with trust in selection, age, education and experience in AI

```
. pwcorr trust_ethical_selection age_group educ_group experienceAI, sig

             | trust_~n age_gr~p educ_g~p experi~I
-------------+------------------------------------
trust_ethi~n |   1.0000
             |
             |
   age_group |  -0.0036   1.0000
             |   0.9696
             |
  educ_group |  -0.0347   0.1931   1.0000
             |   0.7176   0.0423
             |
experienceAI |  -0.0323  -0.0754   0.0381   1.0000
             |   0.7350   0.4296   0.6916
             |
```

T- tests with acceptance in selection with gender (not significant)

```
. ttest acceptance_selection, by(gender_bin)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	37	3.277027	.1558373	.9479213	2.960974	3.59308
1	73	3.313927	.0929781	.7944057	3.128578	3.499275
Combined	110	3.301515	.0805627	.8449482	3.141843	3.461188
diff		-.0368999	.1712664		-.3763797	.3025798

```
    diff = mean(0) - mean(1)                                      t =  -0.2155
H0: diff = 0                                     Degrees of freedom =      108

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.4149         Pr(|T| > |t|) = 0.8298          Pr(T > t) = 0.5851

.
```

Appendix E: Sector *Training & development*

Correlation in the T&D area

Pairwise correlations in T&D

Variables	(1)	(2)	(3)
(1) Acceptance T&D	1.000		
(2) Perceived Ease T&D	0.592*	1.000	
	(0.000)		
(3) Trust T&D	0.408*	0.230*	1.000
	(0.000)	(0.016)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Correlation with acceptance in T&D, trust T&D and experience in AI

```
. pwcorr acceptance_TD trust_ethical_TD experienceAI, sig

             | accept~D trust_~D experi~I
-------------+---------------------------
acceptance~D |   1.0000
             |
             |
trust_ethi~D |   0.4084   1.0000
             |   0.0000
             |
experienceAI |   0.0709  -0.0132   1.0000
             |   0.4616   0.8915
             |
```

Correlation with acceptance, perceived ease of use and trust T&D, experience with AI and age

```
 pwcorr acceptance_TD PE_TD trust_ethical_TD experienceAI age_group, sig

             | accept~D    PE_TD trust_~D experi~I age_gr~p
-------------+---------------------------------------------
cceptance~D  |   1.0000
             |
             |
       PE_TD |   0.5917   1.0000
             |   0.0000
             |
rust_ethi~D  |   0.4084   0.2299   1.0000
             |   0.0000   0.0162
             |
xperienceAI  |   0.0709   0.1858  -0.0132   1.0000
             |   0.4616   0.0519   0.8915
             |
   age_group |  -0.0016  -0.1086  -0.0305  -0.0754   1.0000
             |   0.9864   0.2589   0.7526   0.4296
             |
```

T- test with acceptance T&D and gender (not significant)

```
. ttest acceptance_TD, by(gender_bin)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
0	36	3.740741	.1648639	.9891831	3.406049	4.075432
1	72	3.680556	.0860758	.7303771	3.508925	3.852186
Combined	108	3.700617	.0790481	.821492	3.543914	3.857321
diff		.0601852	.168374		-.2736327	.394003

```
    diff = mean(0) - mean(1)                                      t =   0.3574
H0: diff = 0                                     Degrees of freedom =      106

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.6393         Pr(|T| > |t|) = 0.7215          Pr(T > t) = 0.3607
```

Regression for H5

```
. reg acceptance_TD i.age_group i.gender_bin i.educ_group i.background_group c.experienceAI c.PE_TD##c.trust_ethical_TD, robust

Linear regression                               Number of obs     =        106
                                                F(12, 93)         =      10.21
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4527
                                                Root MSE          =     .64094
```

acceptance_TD	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
age_group						
2	.1057494	.1339572	0.79	0.432	-.1602631	.3717618
3	-.0103016	.2984284	-0.03	0.973	-.6029213	.5823181
1.gender_bin	-.0690439	.1726072	-0.40	0.690	-.4118076	.2737199
educ_group						
2	-.1236686	.210452	-0.59	0.558	-.5415844	.2942473
3	.0569404	.2295838	0.25	0.805	-.3989676	.5128484
background_group						
2	.0943954	.184513	0.51	0.610	-.2720109	.4608017
3	.1560683	.2355356	0.66	0.509	-.3116587	.6237952
4	.0213719	.1952119	0.11	0.913	-.3662803	.4090242
experienceAI	-.0389438	.0849373	-0.46	0.648	-.2076124	.1297247
PE_TD	.9063905	.1827321	4.96	0.000	.5435207	1.26926
trust_ethical_TD	.8596815	.2533882	3.39	0.001	.3565027	1.36286
c.PE_TD#c.trust_ethical_TD	-.1474423	.0704085	-2.09	0.039	-.2872595	-.007625
_cons	-.578588	.7005056	-0.83	0.411	-1.969653	.8124774

Appendix F: Acceptance Overall as DV

Regression for H6

```
. reg acceptance_overall i.age_group i.gender_bin i.educ_group i.background_group c.experienceAI, robust

Linear regression                                   Number of obs     =        109
                                                    F(9, 99)          =       1.48
                                                    Prob > F          =     0.1644
                                                    R-squared         =     0.1033
                                                    Root MSE          =     .60382
```

acceptance_ove~l	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
age_group						
2	-.2418697	.1329759	-1.82	0.072	-.5057228	.0219834
3	-.0366309	.226326	-0.16	0.872	-.4857108	.412449
1.gender_bin	.1151998	.181926	0.63	0.528	-.2457809	.4761804
educ_group						
2	-.2108329	.1651024	-1.28	0.205	-.538432	.1167661
3	-.1295488	.1866804	-0.69	0.489	-.4999632	.2408657
background_group						
2	.172449	.1664917	1.04	0.303	-.1579065	.5028046
3	-.1552233	.2304011	-0.67	0.502	-.6123891	.3019424
4	-.3106256	.19334	-1.61	0.111	-.6942541	.0730029
experienceAI	-.012742	.0661635	-0.19	0.848	-.1440248	.1185408
_cons	3.889224	.2250857	17.28	0.000	3.442605	4.335843

Regression with acceptance and trust overall and experience with AI

```
. reg acceptance_overall c.experienceAI trust_ethical_overall, robust

Linear regression                                   Number of obs     =        112
                                                    F(2, 109)         =      35.34
                                                    Prob > F          =     0.0000
                                                    R-squared         =     0.4819
                                                    Root MSE          =     .45654
```

acceptance_overall	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
experienceAI	.049105	.0497755	0.99	0.326	-.0495485	.1477585
trust_ethical_overall	.6498451	.0785138	8.28	0.000	.4942334	.8054569
_cons	1.601127	.2942957	5.44	0.000	1.017842	2.184411

Regression with acceptance overall and control variables

```
. reg acceptance_overall i.age_group i.gender_bin i.educ_group i.background_group, robust

Linear regression                               Number of obs     =        109
                                                F(8, 100)         =       1.57
                                                Prob > F          =     0.1426
                                                R-squared         =     0.1030
                                                Root MSE          =     .60088

------------------------------------------------------------------------------------
                 |               Robust
acceptance_ove~l | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-----------------+------------------------------------------------------------------
       age_group |
              2  |  -.2395436   .1361143    -1.76   0.081    -.5095906    .0305034
              3  |  -.0306241   .2347871    -0.13   0.896     -.496435    .4351868
                 |
    1.gender_bin |   .1154666   .1801868     0.64   0.523    -.2420189    .4729521
                 |
      educ_group |
              2  |  -.2035448   .1639142    -1.24   0.217     -.528746    .1216564
              3  |  -.1289332   .1852728    -0.70   0.488    -.4965092    .2386427
                 |
background_group |
              2  |    .171765   .1653943     1.04   0.302    -.1563727    .4999027
              3  |  -.1522313   .2328074    -0.65   0.515    -.6141145     .309652
              4  |   -.310404   .1927504    -1.61   0.110    -.6928154    .0720073
                 |
           _cons |   3.853779   .1583138    24.34   0.000     3.539689    4.167869
------------------------------------------------------------------------------------
```

Appendix G: Trust as DV

Regression with trust T&D as DV

```
. reg trust_ethical_TD i.age_group i.gender_bin i.educ_group i.background_group, robust

Linear regression                               Number of obs     =        106
                                                F(8, 97)          =       1.78
                                                Prob > F          =     0.0899
                                                R-squared         =     0.1235
                                                Root MSE          =     .69982
```

trust_ethical_TD	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
age_group						
2	-.3667814	.1734722	-2.11	0.037	-.7110757	-.0224872
3	-.0914385	.2377475	-0.38	0.701	-.5633014	.3804244
1.gender_bin	.133067	.1875168	0.71	0.480	-.2391019	.5052359
educ_group						
2	-.1481045	.1839951	-0.80	0.423	-.5132838	.2170748
3	-.049984	.2167443	-0.23	0.818	-.4801614	.3801935
background_group						
2	.1027381	.1923626	0.53	0.595	-.2790484	.4845247
3	-.2842296	.2342959	-1.21	0.228	-.7492422	.180783
4	-.5163291	.2181371	-2.37	0.020	-.9492708	-.0833873
_cons	3.389049	.2227346	15.22	0.000	2.946982	3.831115

Regression with trust selection as DV

```
. reg trust_ethical_selection i.age_group i.gender_bin i.educ_group i.background_group, robust

Linear regression                               Number of obs     =        109
                                                F(8, 100)         =       1.02
                                                Prob > F          =     0.4253
                                                R-squared         =     0.0685
                                                Root MSE          =     .73396
```

trust_ethical_~n	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
age_group						
2	-.1655615	.1624505	-1.02	0.311	-.4878586	.1567355
3	-.0601108	.2527398	-0.24	0.812	-.5615394	.4413178
1.gender_bin	.0423985	.1988006	0.21	0.832	-.3520162	.4368132
educ_group						
2	-.2130718	.2077467	-1.03	0.308	-.6252353	.1990916
3	-.151266	.2574491	-0.59	0.558	-.6620377	.3595057
background_group						
2	.200489	.2123399	0.94	0.347	-.2207873	.6217653
3	-.1013183	.2401506	-0.42	0.674	-.5777702	.3751337
4	-.3356888	.2199089	-1.53	0.130	-.7719818	.1006042
_cons	3.100933	.1981212	15.65	0.000	2.707866	3.493999

Regression with trust in recruitment as DV

```
. reg trust_ethical_recruitment i.age_group i.gender_bin i.educ_group i.background_group, robust

Linear regression                               Number of obs     =        108
                                                F(8, 99)          =       0.62
                                                Prob > F          =     0.7550
                                                R-squared         =     0.0577
                                                Root MSE          =     .67809
```

trust_ethical_~t	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
age_group						
2	-.1289707	.1477576	-0.87	0.385	-.4221538	.1642125
3	-.0399667	.2435266	-0.16	0.870	-.5231763	.443243
1.gender_bin	.05789	.1988163	0.29	0.772	-.3366048	.4523847
educ_group						
2	-.1885604	.2018047	-0.93	0.352	-.5889848	.2118639
3	-.2289838	.250907	-0.91	0.364	-.7268376	.2688701
background_group						
2	.241552	.2139574	1.13	0.262	-.1829859	.66609
3	-.1268522	.2349197	-0.54	0.590	-.5929838	.3392794
4	-.1520701	.2111814	-0.72	0.473	-.5710999	.2669596
_cons	3.010529	.1841975	16.34	0.000	2.645042	3.376017

Appendix H: Abstract in German

Die rasante Entwicklung Künstlicher Intelligenz (KI) hat zu einem Wandel in zahlreichen Bereichen der Arbeitswelt geführt, darunter auch im Human Ressource Management (HRM). Diese Masterarbeit untersucht, wie das Vertrauen der Mitarbeiter in KI-Systeme ihre Akzeptanz solcher Technologien in HRM-Prozessen beeinflusst, mit besonderem Fokus auf die Bereiche Rekrutierung, Auswahl und Aus- und Weiterbildung.

Als theoretische Grundlage dient das Technology Acceptance Model (TAM), das um die Variable Vertrauen erweitert wird. Zur empirischen Überprüfung der Hypothesen wird eine quantitative Online-Befragung unter Mitarbeitern verschiedener Branchen durchgeführt. Diese Studie analysiert den Einfluss von Vertrauen, wahrgenommener Benutzerfreundlichkeit und verschiedenen demografischen Variablen auf die Akzeptanz von KI in HRM-Prozessen.

Die Daten werden mittels deskriptiver Statistik und multivariater Methoden, insbesondere Regressionsanalysen, ausgewertet. Die Ergebnisse zeigen, dass Vertrauen eine zentrale Rolle für die Akzeptanz von KI-Technologien im Personalmanagement spielt, insbesondere in Situationen, in denen Mitarbeiter wenig Transparenz oder Kontrolle über automatisch generierte und datengesteuerte Entscheidungen haben. Die Arbeit trägt somit zur Weiterentwicklung des Technology Acceptance Model bei und liefert praktische Implikationen für die vertrauensfördernde Einführung und Nutzung von KI-Systemen im Human Ressource Management.