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AI Bias in Recruitment

Gender Equality in Multinational Corporations

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ABSTRACT:
Tämän kandidaatintutkielman tarkoituksena oli selvittää, miten tekoäly vaikuttaa rekrytoinnissa sukupuolten välisen tasa-arvon toteutumiseen monikansallisissa korporaatioissa, sillä tekoälypohjaisen rekrytoinnin vaikutuksia sukupuolten tasa-arvoon on edelleen tutkittu rajallisesti. Aihe on tällä hetkellä tärkeä, sillä tekoälyn käyttö on lisääntynyt yrityksissä ja se näkyy erityisesti rekrytoinnissa. Samanaikaisesti tekoälyn käyttöön liittyy paljon eettisiä kysymyksiä, koskien esimerkiksi sen tuottamaa virheellistä tietoa.

Tutkimusongelmaan vastataan kahden tutkimuskysymyksen avulla. Ensimmäinen kysymys on, mitä on tekoälypohjainen rekrytointi, ja mitkä ovat sen keskeiset hyödyt ja haasteet monikansallisille yrityksille. Toisessa kysymyksessä pohditaan, miten sukupuolten välistä tasa-arvoa voidaan toteuttaa tekoälypohjaisessa rekrytoinnissa monikansallisissa yrityksissä.

Tutkimusaihetta tarkastellaan etenkin HRM kontekstista ja teoreettisena viitekehyksenä tutkielmassa toimivat Dual System Theory, Technology Acceptance Model (TAM) ja Institutional Theory. Tutkimus on toteutettu kirjallisuuskatsauksena ja käytetty akateeminen kirjallisuus on vertaisarvioitua.

Tutkielman tuloksena on, että tekoälypohjainen rekrytointi voi tehostaa ja nopeuttaa rekrytointiprosesseja ja tukea monikansallisten korporaatioiden globaalien HR-prosessien yhdenmukaistamista. Sukupuolten tasa-arvoa on myös mahdollista edistää tekoälyn objektiivisemman arvioinnin avulla ja vähentämällä inhimillisiä ennakkoluuloja.

Samalla tutkimuksessa osoitetaan, että tekoäly ei ole automaattisesti puolueeton, vaan se voi vahvistaa olemassa olevia vinoumia, jos sitä koulutetaan vinoutuneella datalla tai sitä ei valvota ja kehitetä riittävästi. Monikansaalisille yrityksille nähdään haasteena erilaiset lainsäädännöt, eettiset kysymykset sekä tekoälyn käyttöönoton ja valvonnan monimutkaisuus.

Sukupuolten tasa-arvon toteutuminen tekoälypohjaisessa rekrytoinnissa edellyttää strategista ja vastuullista lähestymistapaa, jossa korostuvat laadukas ja puolueeton koulutusdata, järjestelmien säännöllinen auditointi sekä rekrytoijien osaaminen tekoälyn kriittisessä käytössä. Tasa-arvo ei siis synny automaattisesti, vaan se vaatii aktiivista suunnittelua ja jatkuvaa seurantaa.

KEYWORDS: Artificial Intelligence Bias, Artificial Intelligence Recruitment, Gender Equality, Multinational

Contents

1 Introduction

As the use of artificial intelligence becomes more widespread, it has also begun to be used in recruitment. According to Kumar et al. (2025, pp. 1746–1747), AI tools reduce the time and costs involved in the recruitment process and improve accuracy, which leads to their growing adoption. While some organizations develop their own systems, many rely on external software solutions that include AI-driven features.

Particularly in large organizations, AI has become a significant tool in recruitment. In high-volume recruitment processes, AI can take over tasks such as pre-qualification and initial screening of applicants.

Despite its efficiency benefits, the use of AI in recruitment has also raised significant ethical concerns. Increasing evidence suggests that AI systems may create bias or generate unfair outcomes. Maintaining stakeholder trust requires careful consideration of fairness in algorithmic decision-making and the prevention of discriminatory outcomes. (Liu et al., 2022, p. 4:14).

The thesis has utilized AI tools to support the work. The Keenious program was used to search for sources, while ChatGPT and Microsoft Copilot were used to brainstorm headlines and paragraph content, as well as to outline the structure. AI was not used to produce the actual analysis or research results, but only to support the planning of the work and information retrieval.

1.1 Background and Relevance of the Study

The growing adoption of AI in recruitment has attracted increasing attention in academic research. Scholars have examined both the potential benefits and the emerging challenges associated with AI-based hiring systems.

Previous research highlights that AI-based recruitment systems automate repetitive sourcing and screening tasks, increasing operational efficiency and enabling recruiters to focus on more strategic activities. Furthermore, the use of data analytics can support more informed decision-making throughout the recruitment process, potentially improving both organizational outcomes and the candidate experience. (Ore & Sposato, 2022, p. 1779).

Empirical evidence has demonstrated how such risks may occur in practice. According to Dastin (2018), the recruitment system that Amazon has been developing since 2014 “did not like women.” The experimental recruitment tool used AI to give candidates grades on a scale of 1–5. In 2015, it was discovered that the system did not evaluate candidates in a gender-neutral manner, as the model was trained on ten years of resumes submitted to the company, most of which were typically submitted by men in the technology sector. As a result, the system appeared to favor male candidates, reflecting the gender imbalance present in the historical data on which it was trained.

These concerns are particularly valid for multinational corporations, given their complex operating environment. Companies operating across multiple countries must comply with diverse legal frameworks and are expected to understand the cultural and social contexts in which they operate. The meaning of gender equality can vary greatly from country to country, which can pose a challenge for the company to act fairly and consistently in recruitment.

These discussions highlight the importance of examining AI-based recruitment not only in terms of efficiency, but also from the perspective of fairness and gender equality. This thesis examines AI-based recruitment in multinational corporations, with a particular focus on its potential implications for gender equality. The study aims to explore how AI recruitment systems are described in existing research and how issues related to fairness and equality are discussed in this context.

1.2 Research Problem and Research Questions

The thesis examines the topic primarily from human resource management (HRM), focusing on multinational corporations that utilize AI in their recruitment processes. As recruitment decisions and the implementation of selection tools are typically governed within HR functions, this perspective is particularly relevant.

Objectivity is important in recruitment, as the candidate's assessment must be unbiased and based on relevant criteria, excluding the HR professional's personal biases or subjective opinions (Rigotti & Fosch-Villaronga, 2024, p. 4). Therefore, it is also important to consider the impact of artificial intelligence on objectivity and examine HR's responsibility in its implementation.

According to Edwards and Kuruvilla (Edwards & Kuruvilla, 2005, p. 10), multinational corporations are rooted in their home country, which creates a country-of-origin effect that means that the institutional system of a multinational company's home country strongly shapes its strategies and operating methods internationally. MNCs also operate simultaneously in different regulatory and labor market environments where equality requirements may vary significantly. Furthermore, multinational corporations must balance global standardization with local adaptation.

In the context of AI-based recruitment, the multinational environment is particularly relevant because algorithmic systems are often developed and standardized centrally, while they are implemented across subsidiaries operating under different institutional conditions. Unlike purely domestic firms, MNCs must ensure that AI-driven recruitment practices comply with multiple legal frameworks and align with varying societal expectations regarding gender equality. This increases the risk that standardized systems may unintentionally conflict with local equality norms, making the governance and monitoring of AI recruitment particularly critical in multinational organizations.

The thesis specifically examines how AI-based recruitment systems affect organizational decision-making and the implementation of gender equality in companies operating in different countries. Although the thesis considers the broader legal and cultural context, the focus is on company practices, i.e., how AI is implemented, managed, and monitored in recruitment and what kind of effects this has on fairness and equality.

The thesis aims to answer the following research questions:

1. What is AI-based recruitment, and what are its key benefits and challenges for multinational corporations?
2. How can gender equality be implemented in relation to AI-based recruitment in multinational corporations?

Since the use of AI in recruitment is a relatively new and rapidly developing phenomenon, research literature on the subject has mainly been published in recent years. For this reason, it is not necessary to strictly limit the publication date of the source material, as most of the relevant research is already topical. The freshness of the topic also highlights that the research field is still developing, and not all the effects of AI on gender equality are yet fully known.

1.3 Definitions of Key Terms

Artificial Intelligence Bias (AI Bias)

AI bias can be categorized into a few broad categories, but what they all have in common is that bias refers to non-neutral outputs in an AI system that can lead to discriminatory outcomes. AI bias can be caused by poor or biased data, choices, and decisions made during the designing of AI, or how people trust and implement the suggestions made by AI. The main types are data bias, development bias, and interaction bias. (Hanna et al., 2025, pp. 3–6).

The potential for small biases in AI systems to cause significant harm is growing as AI systems become more prevalent in critical sectors such as healthcare, law enforcement, and employment (Ferrara, 2024, p. 7) According to Lacmanovic and Skare (2025, pp. 393–394), as society becomes more aware of AI biases and the potential harm of these, concerns about the ethical and responsible use of AI are growing globally. As stated by Lacmanovic and Skare, this has led to demands for greater transparency and accountability, leading to the first laws regarding AI biases.

Artificial Intelligence (AI)

Artificial intelligence refers to a machine-based system. It generates output, such as decisions, content, etc., from the input it receives. AI systems have different levels of autonomy and adaptiveness, depending on the system. (OECD, 2024, p. 4).

Artificial Intelligence Recruitment (AI Recruitment)

AI recruitment refers to recruitment that uses AI-based solutions, such as chatbots, predictive analytics, and resume screening algorithms. These solutions streamline decision-making, and the use of AI in recruitment has had a positive impact on efficiency, accuracy, and applicant distribution, among other things. However, the problem is the biases of the algorithms and the questions of fairness. (Kumar et al., 2025, pp. 1741–1742).

Gender Equality

According to UNESCO (2014, p. 11), gender equality refers to a situation where both sexes have equal rights, responsibilities and opportunities. This also means recognizing the diversity of different groups of women and men, including by considering their interests, needs, and priorities.

Multinational corporations (MNCs)

In the past, multinational corporations have been seen as successful and large internationally operating organizations that have grown and established their position over the years. The operations, vision, and strategies of these companies have also been international. However, due to technological innovations, large sizes are no longer a prerequisite

for multinationalism. Nowadays, more companies operate across national borders, and the number of companies that can be classified as MNCs has increased. Alternative theoretical and operational definitions of the term MNC have been proposed, but none of these have become a standard definition. (Aggarwal et al., 2011, pp. 557–558).

1.4 Structure of the Thesis

The thesis consists of five main chapters. The first chapter introduces the topic and objectives of the thesis and presents the research questions. Furthermore, keywords are defined, and the structure is outlined. The second chapter focuses on AI in recruitment. The chapter focuses on how AI can be used in recruitment and in which stages, but it is also compared to the traditional recruitment process. Moreover, AI biases and AI's advantages and limitations are introduced. In this chapter, Dual System Theory is used as a theoretical framework, as it helps to understand the role of AI in recruitment.

The third chapter discusses MNCs' recruitment practices and how they are utilizing AI in recruitment. It is discussed why MNCs are adopting AI in recruitment through external and internal motives. Also, the Technology Acceptance Model and the Institutional Theory are used as theoretical frameworks to understand this adoption. In addition, the chapter explores in more detail what are the challenges and risks of using AI in this context.

The fourth chapter considers what gender equality is in employment and why there is gender inequality in recruitment. The chapter takes into consideration how AI can strengthen gender biases and what MNCs can do to prevent it from happening. The final chapter presents conclusions and answers the research questions. Furthermore, key findings are summarized, limitations outlined and suggestions provided for possible future research.

2 Artificial Intelligence in Recruitment

This chapter reviews what AI in recruitment means, which parts of recruitment it is used in, and how it differs from traditional methods. AI bias is also examined, and the reasons it may develop. Lastly, the advantages and limitations of this AI-based recruitment are introduced.

2.1 AI in Recruitment and Selection

This section examines how AI is used in different stages of recruitment and compares these applications to traditional recruiter-driven practices. The following sub-sections review sourcing, screening, matching, fit assessment, and decision-making, highlighting similarities, differences, and implications for recruitment processes.

2.1.1 Sourcing

Sourcing is the initial stage of recruitment and the phase where algorithmic use has been most widely researched and applied (Fabris et al., 2025, pp. 3–5). Fabris et al. introduce, that this stage involves creating a job posting, where artificial intelligence can be used to create a job description, for example. Algorithms look for similarities between jobs and candidates using rankings and recommend open positions to job seekers (Fabris et al., 2025, pp. 3–5; Sipior et al., 2024, pp. 399–400). According to Fabris et al., AI makes it possible to identify and reach a broad range of candidates while also enabling more targeted job advertising. Social networks also belong to this stage of recruitment, and they are of great importance to both applicants and employers.

2.1.2 Screening

The recruitment process often continues with CV screening, which AI can do mainly independently, providing the recruiter with relevant recommendations. According to Ammupriya et al. (2025, p. 235), AI systems can analyze structurally unorganized documents and form structured data from them. Furthermore, this enables important information

to be collected from the job applicant (Ammupriya et al., 2025, p. 235), and as a result, the recruiter does not have to spend time formatting or searching for information. The algorithms used in the screening have been trained on large numbers of CVs, which helps the algorithms to recognize patterns and assess the candidate's suitability for the role (Albassam, 2023, p. 7). This provides the recruiter with a good starting point for the process, as only the most suitable applicants for the role are separated from the large pool of applicants, leaving more time for the later stages of the process.

Current technological recruitment tools do not understand context very well, which is why current AI models aim to identify better-suited candidates, and they can combine different concepts and keep the classification consistent across industries. AI also helps to standardize the language in the evaluation of applications, and this way, applications written in different ways can be evaluated more fairly. At the same time, anomalies can be detected, for example, in the background information. (Ammupriya et al., 2025, p. 235).

However, companies currently have a particular need to speed up the recruitment process, especially the processing of resumes, because at this stage, the candidate pool is too broad. An example of this is Amazon's recruitment event from 2021, where the company received up to a million applications. With the help of AI, it is possible to speed up the process, and it is also described as a cost-effective solution. (Sipior et al., 2024, pp. 399–400).

According to Gomathy et al. (2022, p. 4), applicant screening is also used in traditional recruitment, and it helps limit the candidate pool, making it possible to focus interview time on the most promising individuals. Screening is said to consider elements including education, prior experience, and professional skills. In accord with Fisher et al. (2022, p. 1), finding suitable candidates from a large and varied pool is identified by over half of talent acquisition leaders as the most challenging aspect of recruitment. They further explain that leaders often decline the candidates presented to them, requiring HR to

continue sourcing additional talent. The difference with utilizing AI is that the traditional process is simpler, but also slower, as finding the right candidates may take a surprisingly long time for the recruiter.

2.1.3 Semantic Matching and Person–Job Fit

According to Ammupriya et al. (2025, p. 236), semantic matching ensures that candidate profiles align with job descriptions. It also considers relevant experience and emotional intelligence in addition to technical expertise and utilizes AI and natural language processing methods. The study notes that when using traditional keyword-based search algorithms, it is important to note that they do not consider contextual variations and differences in wording.

The shortcomings of certain models highlight the need for even more sophisticated approaches that are capable of better inference. For example, the Zero-Shot Learning model can identify connections between job roles and skill profiles that have not previously appeared in the training data. This offers new opportunities to improve efficiency and reduce bias, while supporting more inclusive recruitment. (Kurek et al., 2024, pp. 6–7).

As stated by Abraham et al. (2015, p. 337), when using traditional recruitment methods, the assumption is that an employee whose knowledge, skills, and abilities match the job requirements is a good fit for the role, also known as person-job fit. The basic idea is therefore the same as in semantic matching, but the implementation method is different. In the traditional approach, suitability is assessed mainly based on the recruiter's own interpretation, by comparing the information provided by the applicant with the job description. Semantic matching aims to understand the applicant's skills more broadly, by identifying, for example, meanings, connections and similarities, between different expressions.

2.1.4 Sentiment Analysis and Person–Organization Fit

AI-generated sentiment analysis, which the Ammupriya et al. study considers an unbiased method compared to human analysis, can be used to assess a candidate's fit for the organization. AI can analyze linguistic and textual cues and sentences can be classified as positive, neutral, or negative. Language and text can also reveal a candidate's emotions and level of interest in the job. (Ammupriya et al., 2025, p. 236).

This analysis can also be used in video interviews, using chatbots, etc. AI considers changes in the applicant's tone, pitch, and speech patterns, and voice sentiment analysis can detect their emotional state. Non-verbal communication, such as facial expressions, can be observed through video, which provides additional insight into the applicant's temperament. An applicant's communication patterns can also be inferred from publicly available posts, such as comments they have made. This allows for an assessment of the applicant's alignment with organizational values, as long-term emotional patterns may serve as an indicator of consistent behavior. (Ammupriya et al., 2025, p. 236).

Sentiment analysis can provide useful opportunities for evaluating candidates, regardless, its effectiveness is influenced by several limitations that may reduce the accuracy of the outcomes. The quality of input data plays a crucial role, as incomplete or inaccurate information can lead to distorted results. Furthermore, linguistic challenges in natural language processing, including ambiguity and the handling of negations, complicate the interpretation of emotions and attitudes. The broader context is also essential, since similar expressions may carry different meanings depending on the situation. (Taherdoost & Madanchian, 2023, p. 3).

Although Ammupriya et al. (Ammupriya et al., 2025, p. 236) describe AI-based sentiment analysis as a more objective and therefore less biased method than human evaluation, the limitations show that it is difficult to achieve a completely neutral or error-free interpretation. If the data or model contains biases or interprets language poorly, the results will also be biased.

Person-organization fit (PO) describes how the norms and values of the organization meet the values of the candidate, or in other words, are they compatible. Compatibility can arise from either supplementary or complementary types of fit. This can be assessed, for example, using the Organizational Culture Profile (OCP) method, in which the values of the individual and the organization are prioritized using the Q-sort technique, and the differences between these two profiles are used to form an index of the level of PO fit. The differences or similarities between the value profiles of the organization and the applicant are used to form an estimate of the level of PO fit, and it can be assessed whether the fit is supplementary or complementary. A good PO fit is associated with later job satisfaction, commitment, and lower turnover. (Kristof-Brown et al., 2023, pp. 385–386).

The methods differ in that AI sentiment analysis examines the candidate through emotional and behavioral cues, while PO fit assessment is based on a structural comparison of value profiles. AI-based sentiment analysis interprets the candidate's communication and behavior to assess both their potential values and their fit with the organization, while PO fit assessment is based directly on the correspondence between values and norms.

2.1.5 Predictive Analytics and Decision-Making

By analyzing historical and real-time data, predictive analytics can provide estimates of how well a candidate is likely to perform in a specific role. Research by Ammupriya et al. (2025, p. 237) reveals that in traditional recruitment, hiring decisions are frequently influenced by recruiters' emotions and prior experience, which may result in inconsistent decision-making. Analytics creates connections between recruitment criteria and long-term performance, and the necessary information can be collected from, for example, personnel files and performance reviews.

AI supports predictive recruitment by analyzing textual data from CVs, cover letters, and interviews to detect patterns associated with successful candidates. It can also assess emotional expressions and performance trends to improve forecasting accuracy. In addition, AI models may support career progression predictions and estimate employee retention using methods such as survival analysis. Overall, predictive analytics enhances recruitment decision-making and workforce planning by improving the ability to anticipate candidate success and long-term employment outcomes. (Ammupriya et al., 2025, p. 237).

However, Albassam (2023, p. 7) notes that predictive analytics in recruitment is not without limitations. It may fail to capture all relevant aspects influencing job performance, such as team collaboration or organizational fit. In addition, its predictive accuracy can be constrained by changes in labor market conditions or evolving organizational needs.

According to Koivunen et al. (2019, pp. 3, 9), in traditional recruitment, decision-making is often based on intuition and limited information. Decision-making is also affected by bounded rationality and cognitive biases (Koivunen et al., 2019, p. 4). Time pressure and rush are especially reasons that lead to intuitive solutions, in addition to which the goals may be unclear, and the recruiter does not have a clear picture of what the organization truly needs in the long term (Koivunen et al., 2019, pp. 8–9). Decisions are also often made based on superficial signals, such as job titles and first impressions, and are influenced by impression management, which is difficult for the recruiter to see through (Koivunen et al., 2019, pp. 11–12).

As a result, recruiters often do not have the opportunity to assess the applicant's long-term development potential, career path suitability, or likelihood of staying in the organization, which an AI tool may be capable of. Taken together, predictive analytics allows for systematic long-term forecasting, whereas traditional decision-making remains short-term, intuition-driven, and limited by the recruiter’s cognitive constraints.

2.2 Common AI Biases

According to Fazil et al. (2023, p. 5), various biases, such as gender bias, have been identified in AI algorithms, and they often stem from the data used to train these algorithms. Hanna et al. (2025, p. 3) support this claim, and they highlight that “This can arise due to various factors such as incomplete data, skewed sampling methods, or errors in data recording.”

Data bias arises from both the data and the design of algorithms. Training data can unawares, reflect societal and historical inequalities, and the problem is exacerbated by, for example, fragmented information systems, differences in digital literacy, measurement errors, and uneven representation of groups in the data. During algorithm design and implementation, choices such as feature selection and model weighting may unintentionally reinforce biases present in the training data. This phenomenon is known as algorithmic bias, which may sustain or even intensify existing disparities when the systems are deployed in real-world settings. (Hanna et al., 2025, pp. 3–4).

To reduce potential bias in AI systems, it is essential to ensure careful handling of data throughout the entire development process. This includes reliable data collection, proper validation procedures, transparent model design, and continuous monitoring after deployment to maintain system performance and fairness. (Hanna et al., 2025, pp. 3–4).

Developmental bias occurs when AI models are built and trained on biased or incomplete data. The quality of AI is directly related to the data used, which can be described by the “Garbage in, garbage out” principle. To avoid bias, special attention must be paid to identifying it, reducing it in training data, validation, model development, and deployment. To solve the problem, techniques are being developed that emphasize transparency, accountability, and fairness, with the aim of reducing bias and increasing fairness. An example of this is fairness-aware machine learning. (Hanna et al., 2025, pp. 4–6).

Interaction bias can arise when AI systems are used in ways that affect their performance and impartiality. In working life and education, this can manifest itself as burnout, differentiation, and a reduction in diversity in the field. Biases related especially to recruitment reduce this diversity but also prevent the creation of inclusive learning environments. Therefore, identifying and reducing unconscious biases is important to make recruitment fairer. (Hanna et al., 2025, p. 6).

2.3 Types of AI Biases in Recruitment

Chen (2023, p. 6) introduces that algorithmic bias can occur based on gender, race, skin color, and personality in the recruitment process. Fazil et al. (2023, p. 5) are approximately on the same lines, as according to them biases can be divided into gender, racial, and socioeconomical background, but they are not limited to these.

Liu et al. bring up another perspective, where biases are divided into explicit (direct) and implicit (indirect). Explicit bias refers to a situation where a sensitive characteristic, such as gender, negatively affects the outcome. Implicit bias refers to when externally insensitive characteristics negatively affect the outcome. These insensitive characteristics can, however, be related to sensitive characteristics, as, for example, the place of residence can be related to a person's ethnic background through demographics. (Liu et al., 2022, pp. 15–16).

Liu et al. further divide biases into two different categories: acceptable and unacceptable. Acceptable biases can be explained by various rational reasons. For example, higher salaries predicted for men may be a result of their working more hours per week on average. Unacceptable biases, on the other hand, refer to situations where the bias cannot be rationally justified, which should therefore be avoided in AI tools. (Liu et al., 2022, pp. 15–16).

Based on these different perspectives, Chen's (2023, p. 6) classification provides a clear way to structure algorithmic bias in the recruitment context. It brings together the key manifestations of bias and allows them to be examined as a coherent whole, which is why it is utilized as the basis for the analysis in this study.

According to Chen (2023, p. 6), gender stereotypes have shifted to natural language processing and machine learning, which is why AI tools may exhibit gender bias. Chen highlights that a well-known example is the Amazon recruitment tool, which favored men. Heilman et al. (2024, p. 169) specify that gender bias arises because stereotypes associated with women do not match the demands that are maintained in jobs and fields considered male. They point out that when stereotypical expectations become widely established, they often remain stable over time and can shape the way individuals interpret information, ultimately leading to biased judgments.

As stated by Chen (2023, p. 6), algorithms can learn racial prejudices, which lead to racial bias. Chen highlights that one example is Microsoft’s Tay chatbot, which quickly learned to produce racist and sexist content on Twitter based on user messages. According to Fabris et al. (2025, pp. 8–9), cost-effective advertise optimization and distribution can also cause racial bias, as it affects who sees job ads. As stated by the research, job ads can start to be biased towards certain user groups that correspond to historical stereotypes about these jobs, and this creates further inequality in recruitment.

AI tools may also exhibit biases related to skin color, for example, due to insufficient training. For this reason, Google’s image recognition algorithm incorrectly classified people of color as gorillas. It has also been shown that people with “names that sound like people of color” are less likely to receive invitations to interviews than those with “white names”. (Chen, 2023, p. 6).

In accord with Chen (2023, p. 6), personality biases have also been observed, as algorithms can assess an applicant's personality based on, e.g., word choices or non-verbal gestures. For example, curiosity can be interpreted by the algorithm as a higher probability of changing jobs. As stated by Sipior (2024, p. 404), when personality assessment AI interview tools are used in recruitment, the problems are not just about how personality is assessed. Sipior highlights that a major challenge is how overconfident some recruiters are in these inaccurate assessments, which can lead to decisions being made without sufficient consideration.

2.4 Advantages and Limitations of AI-Based Recruitment

The use of AI in recruitment raises many different opinions, often regarding its advantages and limitations. The purpose of the next section is to examine these advantages and limitations to better understand its uses, as well as its targets. Finally, these factors are also reviewed through the Dual System theory.

2.4.1 Advantages

The use of AI is more effective in screening, as it extracts information more accurately and efficiently, thus also reducing manual and time-consuming procedures. AI uses semantic matching to improve job–candidate alignment by identifying contextual relationships between applicants' profiles and job roles. Predictive analytics can enhance recruitment outcomes by increasing the likelihood of successful hires and supporting improved employee retention. AI-based bias mitigation techniques can support fair and ethical candidate evaluation by helping to reduce discriminatory hiring practices. (Ammupriya et al., 2025, p. 239).

Chatbots used in the early stages of recruitment can expand the candidate pool and accelerate the hiring process. In comparison with traditional approaches, AI-based methods have also been associated with improvements in accuracy, precision, consistency,

and fairness. Overall, the use of AI in recruitment may enhance the quality of hires and contribute positively to organizational performance. (Ammupriya et al., 2025, p. 239).

2.4.2 Limitations

Islam (2024, p. 16), highlights that AI systems may reproduce biases linked to factors such as race, gender, and socioeconomical background. At the same time, achieving fairness in AI-driven decision-making is not straightforward, as it involves complex methodological and ethical challenges. According to Magham (2024, p. 466), increasing complexity in AI models makes full explainability more challenging, highlighting the need to balance performance with interpretability. As stated by Magham, this is especially emphasized in recruitment, as it often requires the use of advanced algorithms, whose decision-making processes are less transparent than those of simpler models.

The increasing complexity of AI models can raise cognitive load and make explanations difficult to understand, particularly for non-technical stakeholders. This may reduce trust in the system. In addition, ensuring model explainability requires significant time and resources, which can prolong and complicate the recruitment process. (Magham, 2024, pp. 466–467).

Lack of market readiness poses challenges, particularly through regional regulation. The EU's strict General Data Protection Regulation (GDPR) makes it difficult to use AI solutions, while lighter regulations in the US reduce this barrier. There may also be a lack of cultural readiness, which limits adoption. (Roppelt et al., 2024, p. 2994).

Based on this, it can be stated that AI is ultimately a complex decision-making support system, and not just a tool for increasing efficiency. Decision-making is therefore not simplified but rather becomes more complex. MNCs must balance benefits and risks when utilizing it in recruitment. In addition, constraints can either slow down or guide adoption. AI also brings a need for new skills requirements for HR, and it requires strategic and considered implementation from companies.

2.4.3 Dual System Theory

Humans have two different cognitive processing systems, the automatic system and the analytical system. The automatic system is described as fast, intuitive, associative, and experience-based. It often produces responses based on heuristics, known also as shortcuts. The analytical system is described as slow, requiring conscious effort, and based on rules and logical thinking. This processing system enables the application of normative models, such as logic, probability, and decision theory. (Stanovich & West, 2000, pp. 645–646, 648–650).

This theory explains why people's responses often differ from normative models. The main reason is seen as the fact that the automatic system produces a quick, intuitive response, which the analytical system does not always correct. This is a consequence of limited capacity, insufficient motivation or understanding, or the task being interpreted differently than the researcher assumes. The task may also require decontextualization, i.e., it must be detached from the everyday situation and one's own feelings and thoughts about purely through rules or logic. (Stanovich & West, 2000, pp. 645–650).

Dual System Theory helps to understand the role of AI in recruitment. Traditionally, decision-making is often based on automatic thinking, which is fast and intuitive but prone to bias. AI can support analytical thinking by providing data-based and systematic assessments, which can improve the objectivity of decisions.

However, these benefits are not guaranteed. If AI-generated information is too complex or difficult to interpret, it may go unused, leading decision-making to rely more on intuition. There is also a risk of bias in AI outputs. Overall, the effectiveness of AI in recruitment depends not only on the technology itself but also on how well users can understand and apply its outputs.

3 AI-Based Recruitment as a Tool in MNCs

The use of AI in recruitment is a broad concept, influenced by various background factors in the MNC context. The following sections discuss why AI is used in these companies, what motivations MNCs may have for using AI, and what challenges and risks are associated with its use. The Technology Acceptance Model and Institutional Theory are used as frameworks when reviewing companies' motivations for using AI in recruitment.

3.1 The Importance of Using AI in Recruitment in MNCs

Recruitment practices in MNCs are shaped by local and global approaches, and it is up to the company to what extent and how these approaches are applied. Recruitment also plays a key role in how MNCs consider diversity and inclusion as part of HRM. The following subsections discuss the needs that corporations have for the use of AI from these perspectives.

3.1.1 Local vs Global Approaches and Cultural Influence

Corporate culture influences how recruitment is carried out in different countries. Recruitment is not just about hiring employees, it also includes how the company attracts applicants, selects employees, and what criteria are used. (Coculʼová, 2015, pp. 50–51).

In MNCs, recruitment practices vary depending on how much freedom is given to subsidiaries. Often, subsidiaries are allowed to use local recruitment methods (polycentric approach), in which case recruitment adapts to the local culture and labor market. Alternatively, the company can use the same practices everywhere (ethnocentric approach), but this is less common. Alternatively, MNCs can combine these by using a geocentric approach. (Coculʼová, 2015, p. 56).

In practice, this means that in recruitment, the company must take local customs, laws, and culture into account, for example, in job advertisements, the selection process, and employee evaluation. Therefore, before transferring recruitment practices to another country, it is important for the company to analyze the target country and choose the appropriate approach. (Coculʹová, 2015, pp. 49, 56).

3.1.2 Diversity and Inclusion

According to Appoh et al. (2024, p. 2271), in MNCs, the importance of diversity and inclusion is crucial due to the global operating environment, and promoting these brings numerous benefits to corporations. As stated by Fonseca & Kogut (2023, pp. 12–13), increasing inclusion can improve corporate culture and rise employee awareness of developing the work environment. Moreover, as reported by them, a diverse and inclusive work environment is believed to benefit the company by, for example, attracting talent, improving the company's reputation, and supporting business success. Appoh et al. (2024, p. 2271) also highlight that recruitment has a huge impact in promoting diversity and inclusion.

Corporations should therefore emphasize that candidates come from different backgrounds and underrepresented groups. This is achieved, for example, through targeted communication and by participating in recruitment events and networking opportunities. Cooperation with organizations that promote diversity is also seen as a good way. (Appoh et al., 2024, p. 2271).

Inclusive job advertisements are essential in reducing bias in recruitment. To avoid discrimination, job postings should be designed to emphasize required skills and competencies instead of personal attributes such as gender or other background characteristics. (Appoh et al., 2024, p. 2271).

It would be beneficial to have diverse representatives from the corporation in interviews to ensure that all applicants are assessed fairly. This can also reduce unconscious prejudices, which can be decreased with training targeted at recruiters. Training programs should emphasize inclusive interviewing practices as well as the role of diversity and inclusion in recruitment decision-making. (Appoh et al., 2024, p. 2271).

Since the complex operating environment of MNCs brings its own challenges, AI can be used as a tool to deal with this complexity. AI has the potential to standardize processes, but also utilizes local data, which helps to achieve balance. When used correctly, it could also support multiculturalism and can enable efficient applicant flow management, which can be seen as a broad advantage in large corporations.

3.2 The Adoption of AI in Recruitment in MNCs

The adoption of AI in recruitment is driven by both external and internal motives. External motives are influenced by, for example, the labor market and digitalization, while internal motives are influenced by factors such as competitiveness and the development of recruitment processes. In addition, the Technology Acceptance Model (TAM) specifically reviews individual-level acceptance, while Institutional Theory explains the adoption of AI at the organizational level.

3.2.1 External Motives of AI Adoption

In developed markets, skilled labor shortages are increasingly driven by demographic shifts and evolving employee expectations. This phenomenon is described by the term *war for talent*. COVID has also accelerated this phenomenon. MNCs see the use of AI in recruitment as one solution to this problem. Companies are trying to improve the applicant experience to differentiate themselves from other multinational corporations, attract talent, and maintain their competitiveness. (Roppelt et al., 2024, p. 2993).

The term *applicant boom* describes the opposite situation, where recruitment is challenged by extremely high numbers of applicants. This is common in emerging markets such as China and India. For example, recruiters may receive several hundred applications for a single position, most of which do not meet the requirements set out in the job advertisement. The phenomenon has also been amplified in the wake of the COVID, as employees have lost their jobs or students have not found employment after graduation. (Roppelt et al., 2024, p. 2994).

Digitalization, a trend that has also been boosted by the previously mentioned pandemic, has also led many companies to incorporate AI into their recruitment. It is believed that its implementation can improve the company's image as technologically advanced and therefore make it more attractive to applicants. (Roppelt et al., 2024, p. 2994).

3.2.2 Internal Motives of AI Adoption

Securing competitiveness is one of the internal motives why MNCs have started to utilize AI in recruitment. In practice, securing competitiveness means, for example, that the company saves on costs and reaches more applicants through recruitment. Cost efficiency can be improved with the help of AI, as the recruitment process is thus reduced in terms of manual, repetitive, and administrative tasks. Cost efficiency is particularly important for fast-growing MNCs that suddenly need more experts. (Roppelt et al., 2024, p. 2995).

AI also enables a wider reach that is more accessible. This can help find suitable candidates for specific or rare roles, which benefits companies that do not recruit in such large numbers. Companies that recruit in larger numbers use this to refine the selection of candidates. (Roppelt et al., 2024, p. 2995).

It has also been observed that the use of AI in recruitment improves objectivity and makes it fairer. It also reduces human error and supports diversity. AI accurately finds the talent a company is looking for and can even estimate how long a candidate will stay with the company by combining information from different sources. (Roppelt et al., 2024, p. 2995).

Benefits are also seen in terms of HR and recruitment work. It improves the motivation of those working in recruitment, as AI removes repetitive tasks, allowing them to focus on more strategic work tasks. This supports the evolution of HR and recruitment roles in MNCs, where they become more strategic partnerships. (Roppelt et al., 2024, p. 2995).

3.2.3 Technology Acceptance Model (TAM) in AI Adoption

The Technology Acceptance Model (TAM) explains why people accept and use information systems. According to Davis (1989, p. 319), user acceptance is based on two key factors: perceived usefulness and perceived ease of use.

Perceived usefulness is defined as the degree to which a person believes that a particular system will improve their performance at work. Thus, a user believes that a system with highly perceived usefulness creates a positive link between use and performance. Perceived ease of use refers to the degree to which a person finds a particular system easy to use. The easiest system to use is likely to receive higher acceptance among users than other systems, all other factors remaining the same. (Davis, 1989, p. 320).

According to Davis's (1989, pp. 331–334) regression analyses, perceived usefulness was clearly a stronger predictor of system usage than perceived ease of use, although both factors were significantly correlated with current and future use of the information system. Furthermore, the results suggest that ease of use affects usage partly indirectly by increasing perceived usefulness.

The Technology Acceptance Model (TAM) provides a framework for understanding why MNCs adopt AI tools in recruitment. Through external motives, AI was perceived as useful. In war for talent situations, it helped to identify rare talents faster, improve the applicant experience, and differentiate itself from competitors. In applicant boom situations, AI made it easier to manage a large number of applicants through automation.

From a TAM perspective, this motivated companies to use AI, as it was seen as directly improving recruitment performance. Digitalization and the effects of the pandemic highlighted the role of AI and strengthened its usefulness for organizations.

Internally, AI supports companies in maintaining their competitiveness, expanding reach, and helping to find suitable candidates for specific roles. It also increases objectivity, fairness, and diversity in recruitment. The benefits of AI are internalized as part of HR processes and strategic thinking, as it streamlines recruitment, reduces manual and repetitive tasks, and frees up time for strategic work. According to TAM, this usefulness makes the tool attractive and increases its use in the organization.

Almeida et al. (2025, pp. 20–22) also found that recruiters find AI tools useful, but the importance of ease of use varies. According to the study, recruiters find AI tools useful and mostly easy to manage, but the main reason for using them is that they improve work efficiency and facilitate the recruitment process, not just that they are easy to use. Younger users and those who are more accustomed to technology find ease of use less critical, but older users may find it more important.

The results of the study are in line with the Technology Acceptance Model (TAM), as both perceived usefulness and ease of use were considered. However, the results show that usefulness appears to be a stronger factor in the adoption of AI in recruitment, while ease of use plays a more supportive role (Almeida et al., 2025, p. 18). This is in line with the central idea of TAM, according to which ease of use affects use partly indirectly by increasing perceived usefulness (Davis, 1989, pp. 331–333).

3.2.4 Institutional Theory in AI Adoption

Institutional Theory consists of three main principles. Coercive isomorphism explains the conformity of organizations due to coercion and regulation. Mimetic isomorphism explains that organizations imitate each other to reduce uncertainty, and normative isomorphism explains that conformity arises through professionalization, i.e. through education, professional standards, and networks. (DiMaggio & Powell, 1983, pp. 150–153).

The central claim of the theory is that organizations do not align for efficiency but for legitimacy. In short, companies choose the same structures because structures perceived as legitimate increase acceptance, stability, and the likelihood of survival. This explains why organizations can appear similar even though their operating environments or goals differ. (DiMaggio & Powell, 1983, pp. 150–151).

Institutional Theory complements the above perspective by explaining why AI is being used in recruitment for reasons other than efficiency. Companies make decisions not only to improve performance, but also to gain legitimacy in their operating environment. This is reflected, for example, in the fact that the adoption of AI solutions is driven by external pressures, such as regulation (coercive isomorphism), competitor actions (mimetic isomorphism), and professional norms and expectations (normative isomorphism).

MNCs may adopt AI because others are doing so or because it is seen as a symbol of a modern and sophisticated organization. In this case, adoption may not be based entirely on perceived benefits, but also on the need to meet environmental expectations and maintain a competitive and credible corporate image. This helps to explain why the use of AI in recruitment is becoming more common in different markets, although its benefits and challenges may vary.

3.3 Challenges and Risks of AI-Based Recruitment

The limitations of AI in recruitment have been discussed previously at a general level, but this chapter will explore the challenges and risks specifically in the MNC context. The challenges and risks can be divided into external and internal, which are discussed in more detail in the following chapters.

3.3.1 External Barriers and Risks

Even among MNCs, there are still no clear and established practices for the implementation of AI, as it is still such a new phenomenon. This raises concerns in companies about how the use of AI appears to the outside world, especially to job applicants. Applicants often expect personal communication, so automated tools in communication can raise suspicions. Therefore, the lack of common practices may be part of the reason why AI has not yet been more widely used in multinational corporations. (Roppelt et al., 2024, p. 2994).

3.3.2 Internal Barriers and Risks

The complexity of organizations can be seen as one internal barrier, which means that MNCs often must build their own backend system for AI solutions. This is challenging because it requires a lot from companies, such as resources, money, and specialized expertise, which are not always available. Expectations for the system can be high and complicated to implement in practice. Implementation also requires the development of human-AI cooperation, which takes time and slows down the implementation of solutions. Moreover, AI is not yet a solution for everything in recruitment, as it makes it difficult to assess, for example, empathy. (Roppelt et al., 2024, p. 2995).

Many corporations have outdated IT systems, which makes it difficult to adopt new technologies such as AI. In recruitment, AI is often not a priority, meaning that companies do not have the systems or data needed for it. Many actors lack an entrepreneurial spirit or desire to develop their operations, which increases their reluctance to change current

practices. This is reflected in a low interest in AI tools, which, in addition to a lack of expertise, can increase distrust and, at worst, resistance to change. Companies also do not necessarily have a clear strategy for AI, meaning that there is only little effort made in it. (Roppelt et al., 2024, pp. 2995–2996).

4 The Impact of AI Recruitment on Gender Equality in MNCs

In this chapter, gender equality in the workplace and the importance of equality in recruitment are considered. It is also reviewed how AI can strengthen gender biases and how MNCs can reduce the impact of it through factors such as AI governance, auditing, and ethical use of AI.

4.1 Gender Equality in Employment

Gender inequality in the workplace continues to be reflected in employment, pay, and leadership positions. These disparities are perpetuated by recruitment practices, where stereotypes, subjective assessments, and networks can place women in an unequal position.

4.1.1 Statistics of Global Gender Inequality in Employment

In 2024, the employment rate for women was 46.4%, compared to 69.5% for men. This represents an employment gap of 23.1 percentage points, and this gap has not narrowed by more than 4 percentage points over 30 years. However, progress has been made, as income gaps have narrowed between 2004 and 2024 across all income groups. Despite this, women still earn significantly less than men, work more unpaid hours, and are more likely to work in informal jobs in low- and lower-middle-income countries. (International Labour Organization, 2025, p. 1).

In 2023, only 30% of women held managerial positions, a figure that has barely changed in 20 years globally, although greater progress has been seen in low-income countries. Women are also vulnerable to sexual violence and harassment in the workplace, which is 1.6 times more likely than it happening for a man. This risk is particularly pronounced among young and immigrant women. (International Labour Organization, 2025, p. 1).

Considering these figures, it is worth highlighting the importance of recruitment in achieving gender equality in the labor market. If recruitment is carried out on an equal footing, without unjustifiably favoring the hiring of men, for example, in management positions or in male-dominated positions, it is already one step closer to a more equal working life.

4.1.2 Gender Inequality in Recruitment

As mentioned earlier, gender inequality is a result of stereotypes that are inherently associated with women, because of which women are not expected to perform as well in masculine fields as men. It has been shown that these existing assumptions also affect evaluation through distorted information processing. The impact has been felt on what information evaluators pay attention to and how they interpret this information. Assumptions are also linked to what evaluators remember about the person. (Heilman et al., 2024, pp. 169–170).

Distorted information processing, the way people are evaluated and interpreted, influences many organizational practices, and the biases associated with it can have far-reaching consequences. In recruitment, however, this directly affects how women are evaluated in the process. (Heilman et al., 2024, p. 170).

It has also been noted that subjective evaluation criteria are, in part, less reliable than clear and measurable criteria. The decision-maker also relies more easily on their own prejudices when the evaluation is based on subjective criteria, which may lead to women being seen as less competent than men. If there are several evaluation criteria, ambiguity may also arise because the evaluator does not know which information should be given the most weight. In this case, a situation may arise in which the evaluator selects and emphasizes information according to his or her own preferences, the selection of which may have been influenced by their own preconceptions. (Heilman et al., 2024, p. 173).

In summary, gender bias in recruitment often arises from stereotypical assumptions and unclear assessment criteria, which can distort information processing and lead to women being evaluated less favorably, especially in male-dominated fields.

4.2 Gender Equality in AI-Based Recruitment

The gender bias produced by AI is therefore typically a result of biased training data. If a company has a historical tendency to favor applicants in a certain way, in this case by gender, it is very detrimental when training AI with this biased data. This will very likely lead to AI favoring those applicants who have succeeded in recruitment in the past, in other words, men. The company itself does not necessarily want the pattern to continue, but to achieve this, corrections to the data must be made, or different training data must be utilized. (Vivek, 2023, pp. 106–107).

Therefore, could be concluded that AI itself does not create gender bias but rather learns to repeat the information fed to it, which has already happened before in history. When properly trained and used, it is even possible to reduce this bias, as AI does not discriminate against anyone in its recommendations, which humans might do.

On the other hand, eliminating bias does not directly lead to equality. Since the use of AI in recruitment is currently focused primarily on pre-selection, it is up to humans to ensure that equality is achieved in the later stages of recruitment. However, if AI provides equal recommendations to recruiters, it will provide a better chance of achieving equality as the recruitment process progresses.

In many countries, the law prohibits discrimination in employment, such as the Civil Rights Act of 1964 (Title VII) in the United States (Sipior et al., 2024, p. 405). This is why it is especially important that AI does not make discriminatory suggestions, for fear of the company using it as a tool suffering legal consequences. Legislation on AI is being developed in many countries and regions, and, for example, a law passed in New York City aims to prevent discrimination by requiring audits of AI recruitment tools (Sipior et

al., 2024, pp. 405–406). Moreover, according to Sipior et al. (2024, p. 405), introduced legislative projects include, for example, the Algorithmic Accountability Act in the United States and the Artificial Intelligence Act in the EU.

These planned laws can support ensuring equality in recruitment, also considering the AI perspective in particular. However, a situation where laws vary significantly between regions or countries can be seen as a challenge, as it may make it difficult to standardize recruitment practices in MNCs and increase complexity. On the other hand, equality may be better ensured locally when legislation is adapted to regional societal challenges.

If gender equality were to be achieved in AI-based recruitment, it could have other, even broader impacts than the fairness of recruitment decisions. Strengthening equality can improve the employer's image and make the company more attractive to job seekers. However, achieving this requires continuous monitoring of AI systems and careful attention to the quality and diversity of training data. Without these measures, there is a risk that existing inequalities will simply be reproduced in a more automated form.

4.3 Promoting Gender Equality in AI-Based Recruitment

Gender inequality is a result of stereotypes that have been associated with women for years. Although AI may reinforce these stereotypes and cause gender bias in recruitment, it can also be seen as a solution to these problems. Traditionally, when recruiting new talent to a company, potentially distorted information processing affects the assessment of candidates, and subjective assessment criteria may lead the recruiter to rely on their own prejudices. This can lead to a situation where recruitment is not based on essential factors and skills, but the applicant can even be assessed based on gender. If AI is used as a tool in recruitment, it is possible to reduce this human-based subjectivity, as AI is based on predefined and standardized assessment criteria.

However, it is important to note several limitations and conditions. AI must be trained on unbiased data, and evaluation criteria need to be defined fairly. In addition, the

model’s decision-making should remain transparent and explainable. Regular testing and updating with new data are also necessary to prevent bias. Currently, many companies use AI mainly in the early stages of recruitment, such as screening, after which recruiters are responsible for ensuring fairness and gender equality. It is also important to balance trust in AI recommendations with human responsibility for final decision-making and critical evaluation

One solution to prevent gender bias is to remove gender-related information from the data. However, this is not entirely problematic, as some information can still provide clues about the candidate's gender and influence the algorithm's decision-making. These include, for example, hobbies and group affiliations. A recruiter can also reinforce these biases if they rely too much on recommendations made by AI. (Vivek, 2023, pp. 106–107).

Recruiting through networks is often presented as an efficient solution for companies because it reduces costs and information asymmetry. However, this approach can also reinforce existing gender imbalances, since decision-makers are often men and their professional networks tend to be male-dominated. When new employees, managers, etc. are selected from these networks, women may be left out before recruitment has even begun. Although some companies try to address this issue by expanding recruitment beyond existing networks, this alternative is often considered less efficient, which limits its wider adoption. (Giannetti & Wang, 2023, p. 503).

Recruitment decisions can be improved when selection is based on objective factors such as skills and education. To achieve this, companies should train HR personnel in the use of AI and ensure they understand its limitations. Organizations should also regularly evaluate AI systems and increase transparency regarding how they make decisions, to ensure fair and reliable recruitment outcomes.

5 Conclusions and Discussion

The study discussed AI-based recruitment in an MNC context, combined with a gender equality perspective. The use of AI in recruitment brought clear benefits to companies, such as efficiency and scalability, but also its own limitations. The limitations included, most importantly, biases and their further strengthening. The recommendations made by AI are not automatically neutral, as achieving them requires a lot of resources, time, expertise, and money. Gender equality is indeed dependent on the implementation of AI.

5.1 AI-Based Recruitment in Multinational Companies: Benefits and Challenges

The first research question was “What is AI-based recruitment, and what are its key benefits and challenges for multinational companies?”. AI-based recruitment refers to recruitment in which AI is used as a tool to make assessments and recommendations. Today, AI can be used in many different stages of recruitment, but it is seen especially as a solution in early-stage recruitment, such as screening, where AI is significantly more efficient than humans.

With the help of AI, it is possible to perform data analytics. Semantic matching aligns candidates’ skills with job requirements, sentiment analysis assesses fit and temperament, and predictive analytics evaluates potential job performance. AI-based recruitment relies on data and algorithms for systematic assessment, making it more structured and potentially more objective than traditional recruitment. According to Dual System Theory, this distinction is important, as algorithmic processing reduces reliance on automatic, bias-prone thinking.

Especially in the MNC context, the benefits of AI are significant. Since corporations often balance local and global approaches, AI can combine these perspectives by enabling standardization at a global level, but at the same time, utilizing local data. This enables

recruitment to be scalable and unified into a global system. Moreover, the management of global HR processes is also made simpler, for example, by means of a unified data structure.

Diversity and inclusion are significant factors for MNCs due to the global operating environment, and AI can promote these related goals. It can help reduce undocumented prejudices that may occur in human-generated evaluations and produce more objective assessments. These enable a broader and more diverse group of applicants to be considered.

The labor market situation varies across regions, which increases the challenges for MNCs. However, AI can help streamline the recruitment process in emerging markets, where large numbers of applicants are common, and conversely, attract more talent and maintain competitiveness in developed markets. A global recruitment system supported by AI also makes it possible to target recruitment more effectively.

Strengthening competitiveness is especially important for fast-growing companies that need more experts quickly. AI enables cost efficiency by reducing manual, repetitive, and administrative tasks. Companies that recruit large numbers of new talent can use AI to refine their candidate selection, thereby shifting the role of HR functions towards a more strategic direction.

The challenges of AI for MNCs are often related to the newness of the technology in question. In practice, this means, among other things, that there are no united practices for its use, and it’s not known exactly what its use will look like to the outside world, for example, to job seekers. Companies often have outdated IT systems in use, and a clear strategy for the use of AI has not necessarily been created yet, which makes implementation even more difficult. On the other hand, there is distrust of technology and AI, and in some situations, also resistance to change, which means that not all companies are even interested in implementing it.

The implementation of AI solutions also has its own challenges, as they require resources, funding, and specialized expertise that not all companies have. It is also important to note that human-AI collaboration must be developed to ensure smooth implementation. Due to the global operating environment, for example, legislation varies by region, which may make it challenging to create a global, unified recruitment system. The implementation may even be incomplete, and the desired benefits may not be fully achieved.

Concerns also arise regarding accountability for AI-related errors, which are further complicated by existing biases and ethical issues. In addition, attention should be paid to external perceptions of AI use and employee acceptance of technology.

5.2 Implementing Gender Equality in AI-Based Recruitment in Multinational Companies

The second research question was “How can gender equality be implemented in relation to AI-based recruitment in multinational companies?”. According to research, gender inequality is common in working life, which is why it is good to consider how the implementation of equality can be considered in AI-based recruitment. As noted in the study, AI can provide a more objective and unbiased assessment, but also reinforce existing biases.

However, it is important to understand that AI does not create more of these biases itself but rather reinforces existing ones. This happens, for example, when AI is trained on biased data, in which case there is an algorithmic bias. In practice, this can manifest itself in the way that AI favors men in the recruitment process when the sector is historically male dominated. How can MNCs then ensure the implementation of equality?

A good starting point can be considered a comprehensive strategy that includes, among other things, the adoption, maintenance, use, and ethical and responsible implementation of AI. To achieve equality, it must be considered already during the introduction. In this case, attention is paid to ensuring that the training data is valid, interpretable,

unbiased and represents different groups evenly. Paying attention to these factors also avoids the emergence and reinforcement of biases, in addition to concretely identifying and reducing biases in the training data. It is important to understand that biases are not always visible but can be hidden in the data or logic.

When implementing AI, it's also critical to remember to test the model and consider whether the system works fairly. The Amazon case illustrates this well, as insufficient testing could have allowed biases to be implemented in practice. AI models can be tested on different groups, e.g., men and women, and see if the algorithm favors one gender. If the model gives different results based solely on gender, it is not equal and requires changes and development.

However, testing should not be left to be performed only at the time of implementation, but should also be done at regular intervals. One viable option is to audit AI systems regularly. Algorithms should also be updated and trained over time.

When using AI, it would be beneficial to consider that recruiters have the necessary training to use it and know how to use the tool critically. Transparency of use is also important, as it can increase trust in the company and, on the other hand, allow the result to be questioned. One way to increase equality is to remove gender-related information from the data. However, this may be difficult, as a lot of information may indirectly indicate gender.

Companies can also decide whether to use AI to assess personality and cultural fit, as this involves an increased risk of bias. A safer option is to use AI only for, for example, pre-selection. At the same time, a particular benefit for multinational corporations arises if AI is programmed to use the same assessment criteria for each applicant. This makes the process more equitable, as recruitment is not based on the assessor's personal view of what is important and what is not.

MMCs have often already strategies for diversity and inclusion, so it would be important for AI models to support these. If the goal is, for example, to get more women into management positions, the AI system should also support this goal. In a situation where a woman and a man are equally qualified for the position in question, AI could therefore recommend a female candidate for the role.

5.3 Limitations and Suggestions for Future Research

One particular limitation can be seen as the novelty of AI, and regarding that, also the novelty of AI recruitment research. AI is also currently developing rapidly, because of which some of the literature may become outdated quickly, and current findings may no longer be valid in the future. Also, the long-term effects are not yet well known, for example, in relation to the situation of gender equality.

Since the topic is discussed in an MNC context, it does not necessarily give a comprehensive picture from the perspective of smaller companies and cannot be generalized to all countries. Differences can be seen between countries, for example in legislation and cultural perceptions of equality. One algorithm does not always work in all environments, and when AI systems are built in different ways in different countries, it is difficult to draw general conclusions.

Because of the earlier-mentioned novelty of AI recruitment research, it would be very interesting to view research into what the use of AI in recruitment can achieve in the long term. Could AI be a solution for a more equal working life, i.e., be used to make recruitment fairer? Research could be carried out, for example, by examining the differences in the implementation of equality between two companies, where one has been using AI in recruitment for a longer time, while the other has relied on traditional methods. Can the differences be seen, for example, in the number of women in the workplace or in management positions?

The lack of common norms and policies also creates many research gaps. Especially in the MNC context, it would be good to consider, for example, whether there is a possibility for a global AI governance model. How could such a global model work, and would it bring significant benefits to companies? An interesting perspective would be who would govern it.

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