The Role of Artificial Intelligence (AI) in Promoting Diversity, Equity, and Inclusion (DEI) in Multinational Organizations

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Abstract

This study explores how Artificial Intelligence (AI) is leveraged to mitigate bias and promote diversity in recruitment processes within multinational organizations. Specifically, the risks and potentials associated with the usage of AI in the recruitment process.

While AI has demonstrated potential in promoting fairness in recruitment processes, cases such as the Amazon case, where Amazon's AI-driven CV screening tool discriminated against female candidates due to being trained on historical data, draw attention to the risks and unintended outcomes that arise from the implementation of AI-driven tools.

Using qualitative, inductive research design, this study aims to answer the research question: "How can AI be leveraged to reduce recruitment biases and promote diversity in multinational organizations, and how does employee perception of AI influence its effectiveness in culturally diverse settings?" Data was collected from eleven semi-structured virtual interviews with HR professionals, recruiters, DEI Managers, and AI implementation stakeholders, who have affinity with AI tools, and vary in nationalities. Thematic analysis, supported by Atlas.ti, revealed four key themes: the increasing usage of AI tools in recruitment and HR, the role of AI in bias mitigation, employee perceptions shaped by trust and cultural context, and the need for sophisticated risk mitigation frameworks. While participants acknowledge AI's potential to reduce bias and improve efficiency, concerns were raised about explainability, data quality, user skills, and over-reliance on generic tools.

Findings suggest that successful AI implementation requires not only technological adaptation but also cultural sensitivity, transparency, AI literacy & user training, and human oversight.

This study contributes to a more nuanced understanding of how AI interacts with Diversity, Equity, and Inclusion (DEI) goals in global HR practices and highlights areas for future cross-cultural and regulatory research.

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1. Introduction

Multinational organizations are increasingly integrating Artificial Intelligence (AI) into human resource functions such as recruitment, performance management, and employee engagement. A report by SHRM Labs indicates that approximately 35% to 45% of companies have incorporated AI-driven tools in their hiring processes, with the AI recruitment sector expected to grow at a compound annual rate of 6.17% between 2023 and 2030 (SHRM, 2023). As companies grow and expand operations across diverse cultural and geographic aspects, AI becomes more appealing due to its potential to increase efficiency, promote fairness, and mitigate unconscious bias. Thus, multinational enterprises are the main focus, as they are exposed to culturally diverse organizations and candidate pools. However, as AI becomes more integrated in the decision-making processes, concerns around transparency, trust, fairness, and cultural sensitivity are also growing (Lawrence, 2024).

First, on the importance and increasing efforts of MNE's on DEI initiatives. Multinational enterprises are increasingly prioritising DEI initiatives in response to growing stakeholder expectations, regulatory pressures, and the proven business case for diverse workforces (Hunt, 2015). Research shows that diverse teams enhance decision-making, drive innovation, and improve financial performances, making DEI a strategic tool for global competitiveness (Jackson, 1995; Gomez, 2019). Improved and rational recruitment processes enhance diversity by minimizing bias and ensuring that all candidates are assessed based on consistent, objective criteria. By standardizing evaluations and focusing on qualifications rather than (subconscious) subjective factors, organizations give every applicant an equal opportunity to succeed (Whysall, 2017), and subsequently diversify their candidate selection. Additionally, social movements and public scrutiny have increased the demand for organizations to reflect the values of equity and inclusion in their operations and culture (Helmig, 2016).

AI-driven recruitment tools, including resume screenings, predictive analytics, and algorithmic assessments, promise to streamline hiring and reduce bias by offering data-driven and standardized evaluations (Nyathani, 2021). These systems can analyse datasets without the cognitive shortcuts or stereotypes that often influence human judgments. For instance, AI can reduce bias in job descriptions by eliminating gender-coded language and anonymize CVs to prevent identity-based discrimination (Schiendorfer, 2024). Nevertheless, these technologies are not without limitations.

If trained on historical data that reflect existing stereotypes, AI systems may accidently reinforce those biases. The risk is particularly high with opaque, "black box" models such as deep neural networks, which make accurate predictions, but are hard to interpret (Von Eschenbach, 2021), making it difficult for users to understand or challenge the rationale behind a hiring decision.

Explainable Artificial Intelligence (XAI) has emerged as a key tool to address these limitations. Explainable AI (XAI) techniques empower both developers and end-users to interpret how machine learning mechanisms make decisions. Enabling organizations to identify and correct biases, comply with transparency and accountability regulations, and promote greater trust and acceptance among stakeholders (Arrieta et al., 2020). By offering global and local interpretability, for example, showing which features most influenced a candidate's score, XAI empowers HR professionals to audit decisions and ensure they align with organizational values and regulatory standards. Studies indicate that when hiring decisions are transparent and explainable, employees are more likely to perceive them as fair and trustworthy, which fosters greater acceptance of AI-driven systems (Rai, 2020; Lee, 2018).

However, technical accuracy alone does not guarantee successful adoption. Employee perceptions, particularly around fairness, data privacy, explainability, and the role of AI relative to human judgment, play a crucial role in forming outcomes. According to the Technology Acceptance Model (TAM), individuals are more likely to accept and engage with AI when they perceive it as useful and easy to use. Research in the construction industry confirms that technological traits positively influence both perceived usefulness (PU) and perceived ease of use (PEOU), which are key drivers of AI adoption (Na, 2022). In culturally diverse settings, these perceptions are further complicated by regional values, social norms, and prior experiences with technology. For instance, the article "What factors contribute to the acceptance of artificial intelligence? A systematic review "notes that culture significantly influences the acceptance of AI, with resistance often stemming from traditional or emotional values that AI cannot replicate. For instance, AI was rejected in Christian education in Vietnam due to its inability to provide spiritual comfort (Tran, 2021), and similarly, Burgundy wine producers resisted AI to preserve tradition (Atwal, 2021). Further research suggest that cultural context, including the value placed on human interaction and tradition, can override perceptions of usefulness or ease of use, emphasizing the need for culturally sensitive AI design and implementation (Kelly, 2023).

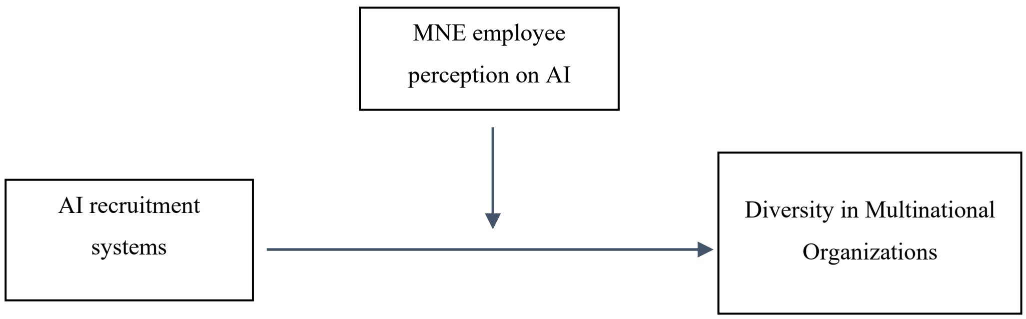
Moreover, scepticism towards AI is often driven by fears of job displacement, surveillance, or lack of recourse in automated decision-making. Research shows that employees feel more comfortable with AI when they perceive it as technology that supports human decision-making rather than technology that replaces it. (Lichtenthaler, 2020). When individuals understand how decisions are made and believe that human oversight is present, their trust in the system increases, resulting in higher engagement, better performance, and greater organizational alignment (Bankins, 2022).

Legal and ethical challenges complicate AI adoption even more. Regulatory frameworks, such as the European Union's General Data Protection Regulation (GDPR) state a "right to explanation" in cases of algorithmic decision-making, emphasising the importance of transparency and user comprehension (Goodman & Flaxman, 2017). In addition, AI systems must comply with anti-discrimination laws, data protection regulations, and evolving standards on algorithmic accountability. As AI becomes more integral to recruitment, companies are under pressure to balance innovation with ethical practises.

While the integration of Artificial Intelligence (AI) into human resource (HR) functions, specifically recruitment, has gained momentum in multinational organizations, current literature offers limited view of how AI affects bias reduction and diversity outcomes. Existing studies emphasise the technical capabilities of AI to automate recruitment tasks and reduce human bias and highlight some of the ethical risks associated with algorithmic discrimination (Dastin, 2018; Albert, 2019). However, less attention has been paid to how AI interacts with human decision makers in real-life settings, where recruiters interpret or overrule AI recommendations, thus shaping final hiring outcomes. In addition, there is limited empirical exploration of how employees perceive AI-driven recruitment systems, specifically how factors such as trust, transparency, and fear of job displacement affect their acceptance and use of these technologies (Amisha Bhargava, 2020). While trust and perceived fairness have been identified as key moderators of AI's effectiveness (Bankins, 2022), these dynamics remain somewhat underexplored in cross-cultural contexts, where cultural values may shape expectations of fairness, transparency, and authority. As a result, the assumption that AI is inherently neutral or universally accepted fails to hold up in practice, especially in global organizations where diverse cultural attitudes toward technology, data privacy, and automation may impact outcomes. This study addresses these gaps by examining not only how AI can be leveraged to reduce bias and promote diversity in recruitment, but also how (MNE) employee perceptions, influenced by cultural context, function as a moderating factor in this relationship. By exploring how AI, cultural diversity, and human judgement interact, this research provides a more comprehensive view of how AI systems function within the complex reality of multinational firms. The findings will contribute to both academic literature and practical knowledge, offering valuable insights for organizations that seek to implement AI ethically and effectively in such a way that it aligns with their Diversity, Equity, and Inclusion goals.

1.2 Problem Statement

"How can AI be leveraged to reduce recruitment biases and promote diversity in multinational organizations, and how does employee perception of AI influence its effectiveness in culturally diverse settings?"



In the proposed model, AI recruitment systems are treated as the independent variable, bias reduction and diversity promotion are the dependent variables, and MNE employee perception functions as a moderating factor that may strengthen or weaken AI's effectiveness across diverse cultural contexts.

1.3 Research questions

1. *How can AI be leveraged to identify and mitigate biases in recruitment?*
2. *How does the implementation of AI influence diversity outcomes in recruitment across multinational organizations?*
3. *How does employee perception of AI within multinational organizations affect its effectiveness?*
4. *What are the risks of AI-driven recruitment tools accidentally reinforcing stereotypes or existing biases, and how can these risks be mitigated?*

2. Literature Review

2.1 Introduction

Artificial Intelligence (AI) is transforming human resource (HR) practices in multinational organizations, particularly in recruitment, talent management, and employee development. This study will take a focus on recruitment. Artificial Intelligence (AI) describes computer systems designed to perform tasks that usually rely on human thinking, such as learning, decision-making, or problem-solving (Iqbal, 2023). In recruitment, AI is often applied through data-driven algorithms, predictive analytics, and machine learning mechanisms that support decision-making. As stated in the previous chapter, AI-driven tools have shown potential in reducing biases during recruitment, by automating tasks such as CV screening, job description optimization, and psychometric testing (Albaroudi, 2024). Tools such as natural language processing (NLP) can be used to interpret CVs and cover letters, while machine learning algorithms can rank candidates-based on pre-defined criteria (Lalwani, 2018; Albert, 2019). Other applications include chatbots for communication with candidates and automated assessments to evaluate skills or personality traits. These technologies aim to increase efficiency and objectivity, potentially reducing the influence of unconscious human bias. However, the effectiveness of these tools is influenced by several factors such as employee perception and the risks of algorithmic bias.

This literature review explores existing research on AI's role in recruitment, with a focus on bias mitigation, enhancing diversity and inclusion, and the challenges of implementing AI in culturally diverse multinational firms. DEI initiatives have become a priority for multinational companies, and AI is increasingly being leveraged to support these efforts. Furthermore, workplace inclusion is positively associated with employee engagement (Sushmita Goswami, 2018), which positively influences organizational performance.

2.2 AI in Recruitment and Bias Mitigation

Recruitment decisions are heavily influenced by implicit prejudice and bias, making those decisions subjective and prone to discrimination (Beattie & Johnson, 2012). Stereotype threat, for example, can lead candidates to underperform due to the anxiety of confirming negative stereotypes, particularly in fields where they are underrepresented. Additionally, selective attention and confirmation bias influence decision-makers by causing them to focus on information that reinforces their initial stereotypes, disregarding contrary evidence. In-group bias further intensifies the issue, as interviewers tend to favour candidates who are similar to themselves, perpetuating homogeneity in organizations. These biases, stereotype threat, selective attention, confirmation bias, and in-group bias, influence the fairness of recruitment processes and limit diversity within organizations negatively (Whysall, 2017).

AI-driven recruitment tools can potentially reduce human biases by providing standardized assessments and supporting decision-making (Chen, 2023). For example, AI-powered applicant tracking systems (ATS) can analyse large volumes of applications and rank candidates based on predefined criteria rather than personal preferences. AI-powered ATS streamline the recruitment process by automating resume screening, enhancing candidate evaluation, reducing biases, and improving efficiency. These systems use technologies such as NLP and AI algorithms to make data-driven hiring decisions and improve both the recruiter and candidate experience (Madanchian, 2024).

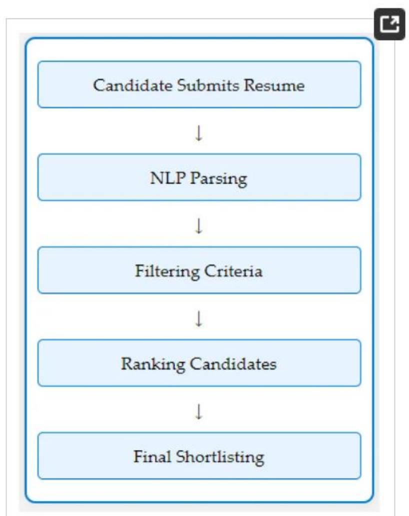


Figure 1. AI-Powered resume screening process.
Source: (Madanchian, 2024)

A very insightful article by Albaroudi et al. discusses how AI techniques can be applied to mitigate biases in hiring processes, but also highlights the limitations and challenges associated with these methods. It presents various AI approaches, including vector space correction and data augmentation, to address algorithmic biases in hiring algorithms. The article also explains the importance of understanding biases in the data and emphasizes the need for fairness in AI systems, while acknowledging the complexities of bias mitigation. Despite the potential benefits, AI tools face limitations, such as overfitting, difficulty in understanding social nuances, and the risk of reinforcing existing biases through training data (Albaroudi, 2024). However, since AI systems may pick up biases from its training data, it is essential to ensure transparency, maintain human oversight where humans make final hiring decisions, and constantly evaluate the system in order to detect and mitigate those biases. Mechanisms such as not relying solely on AI rankings and offering corrective actions are recommended to enhance fairness in AI recruitment (Chen, 2023). Consistent with these concerns, recent research shows the value of hybrid human-AI workflows where humans retain oversight, while AI systems support efficiency and structure. This collaborative model helps mitigate the risks of over-reliance on automated decisions and allows for bias-aware interventions and fairness constraints during candidate screening (Köchling, 2021). A well-documented case is Amazon's AI recruiting tool, which was found to disadvantage female candidates due to biased training data reflecting past hiring patterns (Dastin, 2018). This raises concerns about the importance of algorithm transparency, continuous auditing, and human oversight to mitigate unintended biases.

2.3 Historical Overview of AI in recruitment

Before the integration of Artificial Intelligence (AI), recruitment was predominantly a manual, labour-intensive process characterized by human-driven resume screening, (phone) interviews, and subjective decision-making (Agency Central Ltd, 2025). Hiring managers and recruiters relied heavily on printed CVs, word-of-mouth referrals, and in-person networking events (geographical factors) to identify talent, often leading to inconsistent outcomes and the reinforcement of unconscious biases (Consul, 2021).

The earliest efforts to streamline recruitment processes began with the usage of computers in order to scan candidates resumes in the late 1990s and early 2000s (Kathryn Lookadoo, 2024). However, the screening methods were largely based on keyword matching (Roever C., 1997), meaning that resumes were ranked or filtered according to the presence of specific words or phrases related to job descriptions, with little understanding of context of quality (Maree, 2018).

As technological capabilities advanced, so did the sophistication of recruitment tools. Machine learning algorithms started to be integrated into recruitment platforms for more refined analysis of candidate profiles beyond simple keyword frequency, which include job descriptions, CVs screening, scheduling interviews, primary screens, job offers/descriptions, and pre-onboarding (Rąb-Kettler & Lehnervp, 2019). By analysing data from resumes, and their social media, these early AI applications enabled predictive analytics, automated candidate sourcing, and even preliminary assessments of cultural fit profiles (Vardarlier, 2020).

Despite these advancements, early, and current, AI-driven recruitment technologies were not without limitations. Many systems still suffered from significant biases inherited from the historical data they were trained on, leading to issues such as fairness and representation (Olajide Ore, 2022). Additionally, early automation attempts often lacked transparency, making it difficult for both candidates and recruiters to understand why certain applicants were favoured over others (Grimmelikhuijsen, 2023).

Over time, organizations and technology developers began to focus more seriously on fairness, transparency, and ethical considerations in AI recruitment systems (Mujtaba, 2019). Today’s AI recruitment tools not only aim to automate tasks, but also to enhance diversity, reduce human biases, and improve candidate experience by incorporating natural language processing (NLP) (Devaraju, 2022), explainable algorithms (Balasubramaniam, 2023), and continuous model monitoring.

2.4 AI Technologies and Tools in Recruitment

As AI technologies continue to evolve, a wide range of recruitment tools, that leverage machine learning, natural language processing (NLP), and predictive analytics, have emerged to streamline and enhance the hiring process. These tools are designed to assist recruiters with tasks such as resume screening, candidate matching, initial assessments, and even interview analysis, aiming to improve efficiency, objectivity, and overall candidate experience (Abdul, 2020).

One prominent example is HireVue, an AI-driven video interviewing platform that analyses candidates’ verbal and non-verbal behaviours, such as facial expressions, tone, and choice of words, in order to predict job performance and cultural fit (Zhou, 2024). While initially praised for its ability to facilitate early-stage hiring decisions, HireVue’s video analysis tool faced significant backlash over concerns about algorithmic bias and lack of transparency, leading the company to eventually phase out its facial analysis component in 2021 (Harvis-Nazzario, 2022).

Pymetrics is another notable tool that utilizes gamified assessments based on neuroscience to evaluate candidates' cognitive and emotional traits, matching them to job roles without relying on traditional resumes (Marøy, 2019). Game-based assessments, particularly those powered by AI, aim to evaluate learners based on interaction data and reflection rather than background factors such as prior experience. However, without proper monitoring and debiasing, these algorithms can unintentionally encode and reproduce biases related to characteristics such as gender or gaming experience (Gupta, 2024).

An additional influential player is Eightfold.ai, a platform that applies deep learning algorithms to match candidates to open positions, predict career paths, and even offer internal mobility solutions within organizations (Hoole, 2023).

However, not all AI recruitment tools have been successful or free from controversy. Amazon's experimental AI hiring tool, which was discarded in 2018, became a cautionary tale after it was discovered that the system penalized resumes that included the word "women's," revealing that the AI had learned and replicated historical gender biases from the company's previous hiring data (Winick, 2018).

These examples illustrate that though AI-powered recruitment tools hold significant potential to improve hiring efficiency, objectivity, and diversity outcomes, they also present risks if not carefully designed, validated, and continuously audited.

2.5 Employee perception of AI

As stated in the first chapter, employee perception plays a crucial role in the successful implementation of AI-driven HR tools. Trust in AI-based decision-making is influenced by factors such as transparency, explainability, data privacy, and the perceived role of AI in decision processes. Research shows that employees are more likely to accept AI-driven HR processes when they understand how decisions are made, feel that AI is used to complement rather than replace human judgment, and perceive the process as transparent and understandable. Specifically, individuals' perceptions of AI decision-making are shaped by factors such as trust, role appropriateness, transparency, and the clarity of the decision-making process. Furthermore, employees are more likely to view AI as fair and just when they have a clearer understanding of how AI systems reach decisions and when these systems are seen as unbiased and transparent, with human oversight where necessary to ensure fairness (Bankins, 2022).

The study by Bhargava et al. (2020) discusses such negative perceptions as well, such as fears of job displacement and concerns over data privacy, can diminish the effectiveness and acceptance of AI tools among employees. Employees who perceive AI as a threat to their job security may experience reduced engagement and performance. Concerns about job displacement can lead to resistance to AI-driven changes and hinder the adoption of these systems (Prentice, 2023)

To address concerns and in order to promote acceptance of AI-driven HR processes, organizations must implement AI in a transparent and ethical manner. Research suggests that clear communication about AI's role, safeguards against bias, and opportunities for employee feedback are crucial for building trust. When employees understand how decisions are made and feel confident in the fairness and transparency of the AI systems, they are more likely to perceive AI as a complementary tool rather than a replacement for human judgment, ultimately encouraging positive perceptions of AI in HR processes (Bankins, 2022).

The article “Extremes of acceptance: employee attitudes toward artificial intelligence” highlights that employee attitudes toward AI are key to its successful implementation. While some employees are open to AI, many are sceptical or fearful often due to concerns about job loss. These attitudes can vary depending on the situation, so companies need to actively manage them through transparency, incentives, and hands-on experience to foster positive engagement with AI (Lichtenthaler, 2020).

Cultural context plays a significant role in shaping how employees perceive and interact with AI systems in HR processes (Kelly, 2023). Diverse cultural values influence attitudes toward automation, decision-making authority, and data privacy, which in turn impact the level of trust in AI-driven tools (Gerlich, 2023). Additionally, attitudes toward data collection and surveillance vary cross-culturally, with employees in some regions expressing heightened concerns over how their data is used in AI systems. For instance, the article “Acceptance and Fear of Artificial Intelligence: associations with personality in a German and a Chinese sample” discusses how German respondents showed greater concern for data privacy and were more cautious about delegating decision-making to AI, whereas Chinese participants were generally more accepting of automation and placed higher trust in AI-supported decisions, reflecting deeper cultural attitudes towards authority and technology adoption. (Sindermann, 2022). Furthermore, in high power distance cultures, individuals are more likely to accept AI decisions when these are perceived as a hierarchical authority decision, as individuals in these cultures are more used to following decisions made by those in higher positions of authority. Conversely, in low power distance cultures, people tend to exhibit greater scepticism toward automated decision-making, as autonomy and egalitarian values are prioritised, and demand more transparency, accountability, and opportunities for personal input (Lee T. P., 2024). Research suggests that cultural identity significantly shapes how individuals perceive and relate to AI technologies. People in collectivist cultures are more likely to perceive AI as an extension of themselves, facilitating conformity and group consensus, and therefore may be more receptive to AI-driven decision-making processes. In contrast, those in individualistic cultures often perceive AI as external to themselves, potentially limiting their independence, personal choice, and sense of privacy, which can heighten scepticism and resistance toward automated decisions (Barnes, 2024). These differences affect not only acceptance but also perceptions of fairness, trustworthiness, and organizational legitimacy in using AI for recruitment.

To effectively implement AI in multinational organizations, it is therefore crucial to tailor communication, training, and governance strategies to align with local cultural norms (ÓhÉigeartaigh, 2020).

2.5.1 AI Transparency and Explainability

As stated in the previous sub-chapter, transparency has been revealed to be a crucial factor in employees' trust in AI, leading us to the following concept, XAI. Explainable Artificial Intelligence (XAI) refers to a series of processes and methods that enable users to understand and trust the outcomes generated by machine learning algorithms (Dwivedi, 2023). In the context of recruitment, XAI can significantly improve the transparency and fairness of AI-based recruitment tools by helping HR professionals understand how machine learning mechanisms make hiring decisions. These techniques offer both global and local insights into feature importance, which allows recruiters to detect biases, justify decisions, comply with legal transparency requirements, and ultimately make more balanced and trustworthy hiring choices (Jamal, 2024).

The importance of transparency in AI models stems from the significant risks due to "black box" systems, which make predictions or classifications without providing any understandable rationale. The lack of transparency in "black box" AI systems, particularly those using deep learning, poses significant risks in contexts such as hiring, where unclear decision-making can conceal and reinforce biases that are built into the data. As the article "Explainable AI: From black box to glass box" states, this negatively affects trust, leads to potential discrimination, and creates legal and ethical challenges, making explainable AI (XAI) critical for ensuring fairness and accountability (Rai, 2020).

For instance, deep learning tools used in hiring such as “complex neural networks”, can make highly accurate predictions, but they are often hard to make sense of, which makes it difficult to asses sources on bias or errors (Li, 2022; Aljadani, 2023). In contrast, intrinsically interpretable models, such as decision trees, rule-based systems, Scalable Bayesian Rule Lists, and Explainable Boosting Machines (EBMs), provide transparent and understandable decision pathways, allowing stakeholders to audit and comprehend the reasoning behind AI outputs (Pillai, 2024).

Emerging solutions are focusing on enhancing explainability within HR technologies. Some companies are designing inherently interpretable models or incorporating explainability layers that provide users with simplified summaries of decision factors (Linardatos, 2020). Additionally, regulatory pressures, such as the European Union's GDPR "right to explanation," are pressuring organizations to prioritise transparency in their AI recruitment practices (Goodman, 2017).

Studies suggest that when candidates and employees understand how AI systems work and perceive them as fair, they are more likely to trust and accept the outcomes (Lee M. K., 2018). Therefore, ensuring that AI-driven recruitment tools are not only effective but also explainable is crucial for enhancing trust, promoting fairness, and achieving sustainable adoption in organizations.

2.6 Ethical and Legal Challenges in AI Recruitment

The integration of AI into recruitment practices comes with a range of ethical and legal challenges, particularly for multinational enterprises, which are operating across diverse regulatory and cultural environments. One of the primary ethical concerns relates to the potential for algorithmic bias, where AI tools may unintentionally reinforce existing societal stereotypes or exclude certain groups based on biased training data (Zuiderveen Borgesius, 2018). This issue is prominent in MNE’s where cultural norms and protected characteristics (such as gender, race, or age) vary significantly across countries, making it potentially difficult to create a universally fair algorithm. Furthermore, many AI recruitment systems operate as "black boxes," offering limited transparency into how decisions are made (Pasquale, 2015). This opacity raises questions about accountability and fairness, especially when candidates are rejected based on AI assessments they cannot challenge or fully understand.

From a legal standpoint, MNE’s must navigate various data protection and employment laws. For instance, AI tools that process candidate data may accidentally violate privacy laws such as the

General Data Protection Regulation (GDPR) in the European Union, which requires for transparency, consent, and the right to human intervention in algorithmic decisions (Zuiderveen Borgesius, 2018). In the United States, there is growing scrutiny over the use of AI in employment, with several states enacting or proposing laws to regulate algorithmic hiring tools. For instance, the New York City Local Law 144, which requires companies using Automated Employment Decision Tools (AEDTs) to conduct a bias audit, provide a public notice to candidates that AI tools are being used, and allow candidates to opt out or request alternative evaluation methods (New York City Council, 2021). Furthermore, the EU AI Act, according to Deloitte, is a key regulation ensuring ethical AI use across Europe (Deloitte, 2024). It introduces strict transparency and fairness requirements for recruiters using ai tools, especially for high-risk applications such as hiring. This will require companies to closely monitor and ensure their AI systems comply with ethical and legal standards. These legal obligations can be especially burdensome for global firms that must tailor their AI systems to comply with regional standards, often requiring more oversight and governance frameworks. The lack of unified international guidelines on ethical AI usage complicates the matters even further, leaving MNE’s to interpret and balance multiple, and sometimes contradictory, compliance demands (Kashefi, 2024). Addressing these challenges requires not only technical solutions but also ongoing ethical review, legal consultation, and stakeholder engagement to ensure responsible and inclusive AI deployment in recruitment practices.

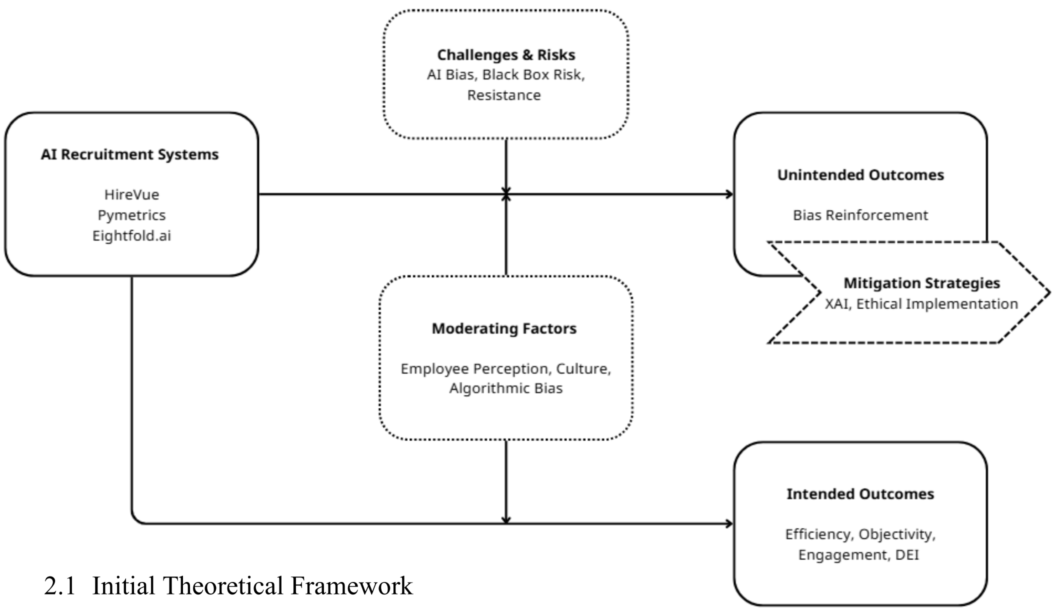
Canada's Proposed Artificial Intelligence and Data Act (AIDA) is another important consideration for multinational organizations. The proposed legislation aims to regulate the development and use of AI systems, with an emphasis on ensuring fairness, transparency, and accountability in AI technologies (Government of Canada, 2022).

The Asia-Pacific region has also shown increasing concern over AI governance. For example, Singapore's AI Governance Framework provides guidelines for organizations to ensure the responsible use of AI: “*The 11 governance principles are transparency, explainability, repeatability/reproducibility, safety, security, robustness, fairness, data governance, accountability, human agency and oversight, inclusive growth, societal and environmental well-being.”* (PDPC, 2023). These guidelines directly influence AI practises within recruitment.

2.7 Theoretical Framework

Based on the theories and content of this Chapter 2, the following theoretical framework is developed.

Reflecting the conceptual model, the theoretical framework illustrates AI Recruitment Systems as the independent variable, Employee Perception as a moderating variable, and Diversity, Equity, and Inclusion as one of the intended outcomes. This theoretical framework addresses additional moderating variables, such as challenges & risks, and it addresses that AI Recruitment Systems may result in unintended outcomes such as bias reinforcement.



2.1 Initial Theoretical Framework

3. Method

In order to answer the research questions regarding how AI can be leveraged to mitigate biases in recruitment and enhance employee engagement while promoting diversity in multinational organizations, this study adopted a qualitative research design. The rationale for this choice is that qualitative research allows for an in-depth exploration of complex and nuanced phenomena (Pervez Ghauri, 2020) such as the intersection of AI and diversity, equity, and inclusion (DEI) efforts in multinational organizations. Given the exploratory nature of this study and the lack of existing in-depth research on employee perception and cross-cultural dynamics in AI implementation, a qualitative design is particularly suitable. Unlike surveys, interviews offer the opportunity for clarification and follow-up questions, which is essential for capturing deeper insights and context-specific experiences (Phellas, 2011).

3.1 Research Design

This study is characterized as qualitative and exploratory research. Qualitative research provides the flexibility required to explore an emerging field, such as AI in DEI initiatives, and to examine the perceptions, experiences, and strategies of key stakeholders (Pervez Ghauri, 2020). By focusing on the "how" and "why" questions of AI adoption in recruitment, this methodology generated insights on the topic of AI systems within MNE's. This study is cross-sectional, as it aimed to capture the perceptions and experiences of stakeholders regarding AI adoption in recruitment at a specific point in time, rather than tracking changes over time (Kesmodel, 2018). Furthermore, this study also adopted an inductive approach, aiming to capture meaningful insights from participants' experiences by identifying patterns and themes directly from the data, allowing for an understanding of how AI is used in recruitment and DEI efforts without solely relying on pre-existing frameworks (Thomas, 2003).

The primary data collection method was semi-structured interviews with key stakeholders, including HR professionals and DEI managers from multinational organizations that have adopted AI-driven tools in their HR practices. These interviews explored the practical application of AI in recruitment, as well as challenges related to bias mitigation and diversity promotion, with an emphasis on how regional and cultural factors influence the effectiveness of AI tools.

The selection of interviews rather than quantitative methods such as surveys is intentional as interviews allowed for the depth, nuance, and adaptability required to explore participant experiences and interpretations, particularly in an area where personal perception, trust, and organizational context play a significant role (Pervez Ghauri, 2020).

3.2 Data Collection

3.2.1 Sampling Strategy

A purposive sampling strategy was used in this study to ensure that the selection of participants consists of participants that are actively engaged in the design, implementation, or evaluation of AI tools in HR practices within multinational organizations. As the article by Taherdoost (2016) notes, purposive sampling is especially suitable for qualitative research where specific individuals or cases are deliberately chosen because they can provide rich, relevant, and diverse insights that cannot be obtained from random sampling (Taherdoost, 2016). This approach is justified in the context of this study, as participants such as HR professionals, DEI managers, and AI developers are uniquely positioned to elaborate on the challenges and opportunities associated with AI adoption in recruitment and diversity efforts. By including participants from various multinational organizations and roles, including HR professionals, DEI managers, and AI developers, the sample captures a wide range of experiences and insights, enhancing the depth and variety of data collected.

The purposive sampling strategy enhances internal validity by selecting individuals with firsthand knowledge and experience of AI implementation in multinational organizations (Tongco, 2007). The diverse multinational sample also improves external validity, as it allows the findings to be more applicable to global AI adoption in HR, offering insights into the role of cultural and regional factors in AI recruitment processes (McEwan, 2020).

While the sample includes participants from diverse roles and organizations, this variation is considered a strength rather than a limitation. As Tongco (2007) argues, purposive sampling benefits from heterogeneous informants when each participant offers relevant insights, thereby enriching the overall quality and scope of the data. Another article argues that methodological diversity and varied fieldwork contexts contribute to richer, more nuanced insights. It discusses that incorporating multiple linguistic and cultural contexts enhances the reliability and depth of findings, a principle that parallels using diverse organizational and professional backgrounds in qualitative sampling (Miestamo, 2016). Participants were selected based on their experience with

AI in multinational or multicultural settings rather than their specific industry, ensuring relevance while maintaining flexibility.

Participants were approached via e-mail, LinkedIn, and personal connections, using a combination of targeted outreach and snowball sampling to ensure relevance and diverse perspectives. Snowball sampling aided with the search of additional participants with the specific expertise required, those directly involved in AI implementation within HR functions, ensuring that referrals were based on existing participants' knowledge of others with similarly relevant insights, thus increasing the relevance and quality of contributions (Parker, 2019).

3.2.2 Data Collection Methods

The primary data source was semi-structured interviews that were conducted virtually, ensuring accessibility and convenience for participants across different regions. Semi-structured interviews allowed for the collection of diverse perspectives while maintaining a structured framework to address the research questions (Pervez Ghauri, 2020). Interviews were recorded, now deleted, with participants' consent to ensure accuracy and enable detailed transcription and analysis (Bottorff, 1994; Garcez, 2011).

As the interviews progressed, the semi-structured approach allows for flexibility in exploring emergent themes that were not anticipated in the initial interview protocol. This adaptability ensured that new insights are incorporated into the data collection process, enhancing the relevance and depth of the data. In the appendix you may find the interview protocols in English and Dutch. The interview questions were developed based on the key themes identified in the literature review, including AI's role in mitigating bias and enhancing diversity. The questions aimed to explore how AI is applied in multinational settings, and how cultural and organizational factors influence its effectiveness.

Participants were informed about the study's objectives and their right to confidentiality before agreeing to participate. Informed consent was given by all participants, who also consented to having their interviews recorded for accurate transcription and analysis (DiCicco-Bloom & Crabtree, 2006). Participants were assured that they could withdraw from the study at any time without consequence, as the Tilburg University thesis guidelines state (University, 2025).

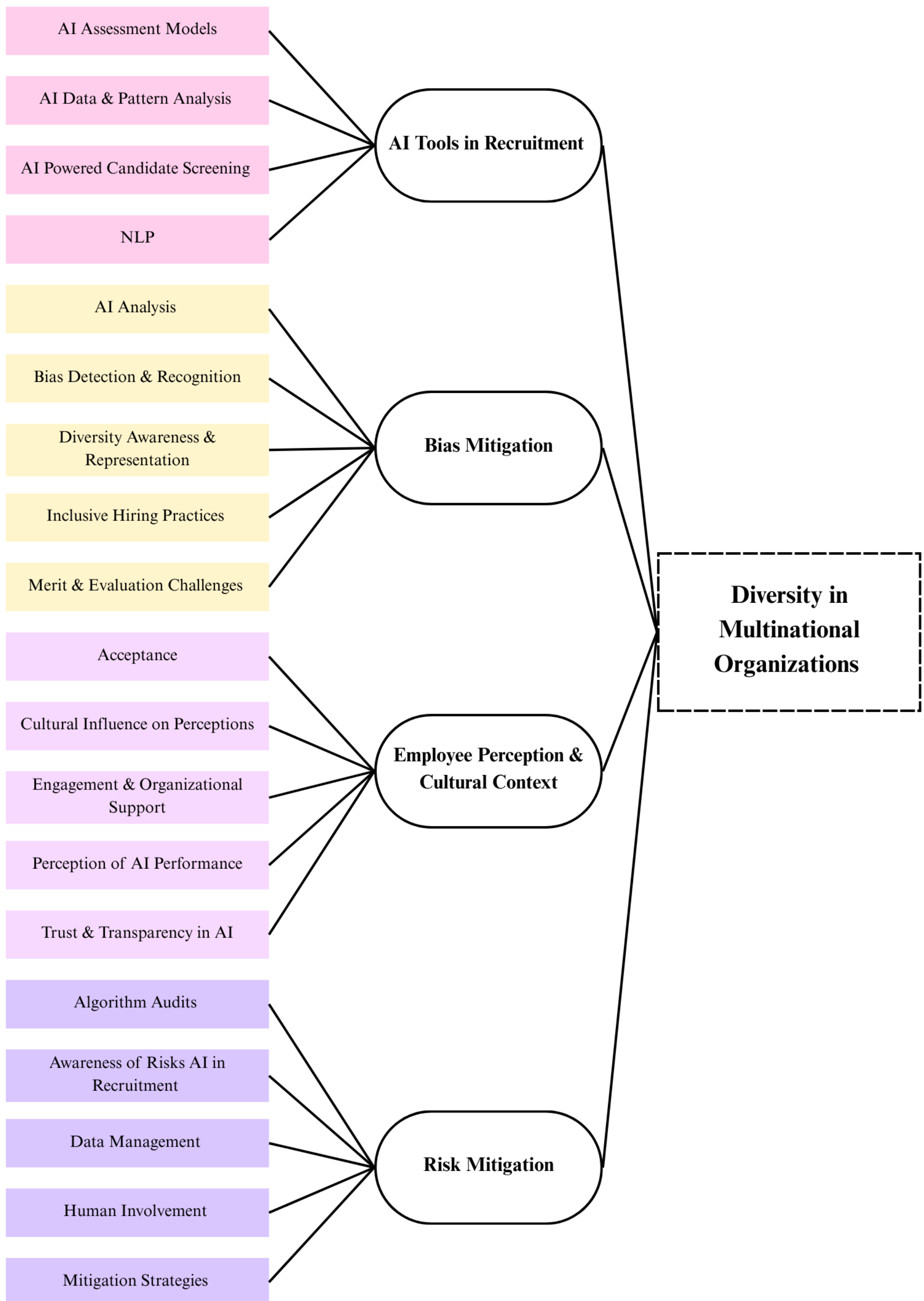
3.3 Data Analysis

Thematic analysis was used to analyse the data, allowing for the identification of key themes, patterns, and insights related to AI's role in DEI, cultural factors affecting AI adoption, and employee perceptions of AI's effectiveness. Thematic analysis involves familiarization with the data through repeated reading of interview transcripts, and coding significant statements and categorizing them into themes (Castleberry, 2018). Emerging themes were identified through iterative coding, where repeated reading and coding of the interview transcripts allowed for the discovery of new themes (Williams & Moser, 2019). These emergent themes were refined and grouped into broader categories to ensure they accurately reflect the research questions and provide a clear understanding of AI's role in DEI efforts.

All transcripts were uploaded and coded using Atlas.ti, a qualitative data analysis software designed to support thematic coding and analysis in qualitative research. The license was obtained through Tilburg University. Atlas.ti facilitated the development of an inductive coding framework, allowing for systematic identification of AI-driven codes, grouping into themes, and clear oversight (Atlas.ti, 2025)

Codes such as "AI in recruitment," "bias detection," "cultural perception," and "governance" were grouped into four main themes based on the coding scheme: AI Tools in Recruitment, Bias Mitigation, Employee Perception & Cultural Context, and Risk Mitigation.

To support transparency, tables were developed summarizing participant responses under each theme, drawing directly from the Atlas.ti output and aligned with the coding scheme presented in Chapter 4. This table provides a structured overview of how each participant engaged with the key research themes, enhancing the clarity and traceability of the analysis.
You may find the tables in the appendix.



3.1 coding scheme

4. Results

This chapter presents the key findings from eleven semi-structured interviews, nationalities ranging from Dutch, French, Indian, Slovakian, Polish, and English, analysed through thematic coding. The results are organized into four primary themes identified in the coding framework: 4.1 AI Tools in Recruitment, 4.2 Bias Mitigation, 4.3 Employee Perception & Cultural Context, and 4.4 Risk Mitigation.

4.1 AI Tools in Recruitment

A prominent theme across the interviews was the growing use of AI tools throughout multiple stages of the recruitment process. Participants described both general-purpose tools such as ChatGPT, Gemini, and Microsoft Co-pilot, and specialized platforms such as Workday, Beamery, Greenhouse, BambooHR, and custom robotic process automation (RPA) systems. These tools were applied for tasks including resume screening, crafting vacancy texts, scheduling interviews, matching candidates to roles, and even conducting assessments or virtual interviews. You may refer to table 4.1 for an overview.

AI Tool Name	*Application in Recruitment Workflow*
Microsoft Co-pilot	Automating email responses, scheduling interviews, document generation
Workday	Resume screening, applicant tracking, interview scheduling, reporting
Beamery	Candidate relationship management, candidate matching, talent pipelining
Greenhouse	Resume screening, interview scheduling, assessment tracking, structured interviewing
BambooHR	Onboarding support, interview scheduling, basic applicant tracking
Custom RPA systems	Resume screening, interview scheduling, data entry, workflow automation

Table 4.1

While some participants had adopted basic AI functionalities, others had integrated them deeply into their hiring systems. For example, Participant 4 detailed a multi-layered process that included CV parsing, personalized follow-up emails, and psychometric evaluation:

"Once you have those 50 CVs... just give the box access to the tool... everything will be personalized." Participant 6 validates this approach, emphasizing AI's role in automating resume selection, interview scheduling, and cultural fit analysis. Similarly, Participant 9, with over a decade of experience, described end-to-end HR management with AI, covering sourcing, screening, onboarding, and internal HR modules through platforms such as SuccessFactors and BambooHR. The goal of these tools is to improve time efficiency by automating recruitment tasks, and to support fair hiring practices by reducing the influence of human bias in early-stage screening.

4.1.1 Practical Applications

Several participants mentioned using ChatGPT and other AI tools in daily tasks such as grammar correction, tone-checking, and role understanding. Participant 2 noted using ChatGPT to refine job postings and emails. Participant 10 described relying on AI to understand unfamiliar technical roles and assist with employer branding (using AI tools to help make the company sound more appealing, inclusive, or professional): "I took their help on my daily recruitment task, as in resume resourcing… it was a great help." This shows us that AI can serve as knowledge aid, particularly when recruiters lack subjective expertise, helping them communicate more effectively with the right candidates. These examples show how AI is not only applied to automate recruitment logistics, but also as a support tool for enhancing human decision-making and communication.

A less commonly discussed but valuable application was in internal talent development. Participant 5 described using AI to match current employees to future roles and suggest skill development paths. This reflects an emerging trend where AI supports not only recruitment but also workforce planning and upskilling. "At Knab Bank… you could search for skills, and the system would help you align with future roles." This shows their recognition of AI's potential in strategic workforce planning, as noted in the results table in the appendix. They viewed AI as not just a recruitment tool, but one that supports long-term talent mobility and internal career development.

4.1.2 Concerns and Limitations

Despite the growing use, many participants acknowledged that AI tools have limitations, particularly when used without customization or critical oversight. Several raised concerns about data quality, lack of nuance, and bias in automated filtering.

Participant 8 described how AI tools might unintentionally exclude candidates without a public online presence: "If your LinkedIn profile is not visible, you will be automatically excluded... That is discrimination against people who value privacy." This illustrates a concern about AI's reliance on digital visibility, revealing how standardized algorithms can unfairly penalise qualified individuals that choose to protect their privacy. Participant 11 criticized recruiters' over-reliance on generic AI platforms such as ChatGPT for resume evaluation: "They take attachments and ask the AI to do the job they should be doing as humans." This reinforces the theme that AI is not a substitute for professional judgement. Even when tools such as Beamery or Workday were used, participants noted that effectiveness depended on how well AI models were trained, whether they were updated regularly, and whether they received human supervision. This point was mentioned by multiple participants, indicating that ongoing human involvement and system maintenance were seen as important aspects of effective AI use.

4.1.3 Trends and Varying Levels of Adoption

Overall, there was a clear trend toward greater adoption of AI in recruitment. However, the level of sophistication varied widely. Participant 1 used AI primarily for language checking, while others, such as Participants 4, 6, and 9, had integrated AI into complex, multi-stage workflows. Participant 4 described a multi-level integration in recruitment, including CV parsing, personalized communication, and psychometric analysis. Participant 6 used various AI functions in screening, selection, and cultural fit evaluation, and participant 9 implemented full-cycle HR tools such as SuccessFactors for sourcing, onboarding, and internal HR processes. Participant 7 observed that most HR professionals are now interacting with AI through integrated systems, whether directly or indirectly. "You set a filter... everyone with 0–3 years of experience and a master's degree can pass. But if you rely only on that, you might miss nuance." This comment shows how surface-level AI applications can miss context, contrasting with participants who applied AI more strategically. This range of practices emphasises that while AI offers immense potential, its impact depends significantly on how thoughtfully and strategically it is applied.

4.2 Bias Mitigation

While the use of AI in recruitment is growing, participants also emphasised that its impact depends not only on efficiency, but also on how fair and responsible it is applied. This led to a second major theme: the role of AI in bias mitigation. The potential for AI to either reduce or reinforce bias in recruitment emerged as a complex and highly nuanced theme in participants' responses. While many acknowledged the promise of AI in mitigating certain forms of human bias, there was a shared caution regarding the risks of transferring existing prejudices into algorithmic systems. The effectiveness of AI in promoting fair recruitment outcomes appears to depend not only on the tool itself but also on how it is designed, implemented, and supervised.

4.2.1 AI as a Tool for Reducing Bias

Several participants identified ways AI can support more objective and inclusive hiring practices. For example, Participant 4 explained how structured, parameter-based recruitment systems limit the potential for bias at the initial screening stage: "When you have parameters, you cannot be biased... that's where it helps to remove bias on the first level of recruitment." This statement reflects the perceived value of parameter-based systems in standardizing early recruitment decisions, aligning with the theme of AI reducing human subjectivity. Participants 5 and 6 emphasized the use of anonymization techniques, such as removing names and photos from resumes to prevent unconscious discrimination. These tools were viewed as particularly valuable in early filtering stages, where human intuition might otherwise influence decisions unfairly. Participant 11 provided an interesting case in favour of AI's capacity to counteract human bias. Referring to a French military project, they explained how AI recommendations led to a higher percentage of female promotions than human supervisors would have made: "The AI would have promoted more women. The gap was 8%, those women were not promoted by human supervisors." Such examples suggest that, when designed with fairness in mind, AI systems can function as corrective mechanisms against deep-rooted human biases.

Despite its potential, participants also expressed significant concerns about AI reinforcing rather than resolving bias. Several noted that bias can be inadvertently embedded in training data, recruitment prompts, or system configurations. Participant 8 raised this issue in relation to gendered job descriptions: “One recruiter said, ‘I like candidates who play chess,’ and biased the system accordingly.” This example illustrates how personal preferences, when built into the recruitment process, can unintentionally introduce gendered or cultural bias into an AI system. Participant 3 worried that imposed diversity targets might backfire by excluding strong candidates or forcing focus on the wrong criteria. They explained that too much focus on demographic characteristics could unintentionally lead to overlooking highly qualified applicant, or reverse discrimination. This reflects the concern that AI systems may become tools for quota fulfilment rather than objective candidate evaluation. Participants 7 and 11 were particularly cautious about over-relying on AI without examining the inputs and outputs. They stressed the need for auditing and accountability, warning that unconscious human biases can still find their way into AI logic, especially if tools are used carelessly.

4.2.2 The Role of Human Oversight

A central conclusion among participants was that human oversight remains essential. While AI can be a powerful tool in reducing bias, its use must be continually monitored and refined. Participant 11 advocated for regular audits and governance frameworks, stating:
“Once you reintroduce the human, you potentially reintroduce new bias. But it is still better than letting AI work unsupervised.” This emphasises the challenge of balancing human judgement with automated systems, reinforcing the idea that complete automation can be more harmful than incorporating human checks, even if those come with their own imperfections. Participant 5 also emphasised the importance of ongoing verification and testing, especially in systems that might evolve or adapt over time: “You must keep verifying it… biases can creep in again.” Their comment suggests that fairness is not a one-time configuration but a continuous process requiring monitoring and adjustments. These insights suggest that AI should not be treated as an automatic solution to bias but as a tool that requires thoughtful configuration, regular review, and ethical oversight. Overall, participants viewed AI as both an opportunity and a challenge in addressing bias within recruitment. While anonymization, structured evaluation, and algorithmic fairness hold great promise, the role of human judgment, ongoing testing, and ethical governance is crucial. The tension between automation and fairness remains a central concern, emphasising the need for deliberate, informed AI integration into hiring processes.

4.3 Employee Perception & Cultural Context

Beyond questions on fairness and bias, participants also reflected on how employees experience and respond to AI technologies in practice. These perceptions were shaped by individual understanding, workplace culture, and communication practices, forming the next theme. Employee attitudes toward these systems have emerged as a crucial determinant of successful implementation. How individuals within an organization perceive and interact with AI tools is influenced not only by their technical understanding but also by broader cultural norms, organizational values, and communication practices.

4.3.1 Trust in AI Systems

Trust emerged as a critical factor shaping employee attitudes toward AI in recruitment. Several participants noted that without a basic understanding of how AI systems operate, employees often respond with uncertainty or scepticism. Participant 4 observed that this fear often stems from a lack of information: “Companies should provide resources, people should use it... trust comes from knowledge.” Showing the importance of educational support and transparency in building trust, as employees are more likely to embrace AI when they understand how it works and how it affects them. Participant 7 reinforced this, emphasising that trust must be actively built through visibility and clear communication about the AI's purpose. They stressed that transparency helps people make sense of AI, which is crucial in building acceptance. This reinforces the idea that employees are not just reacting to technology but to how it is introduced and communicated within the organization. Participant 11 added that demonstrating results, such as efficiency or inclusive hiring outcomes, was one of the most effective ways to earn trust: “Trust is essential… You build trust by showing results, efficiency, capability, inclusive outcomes.” Suggesting that practical, positive outcomes play a key role in building credibility and confidence in AI tools, especially when employees see tangible benefits aligned with organizational goals.

Overall, trust in AI systems was seen as achievable but fragile, heavily dependent on organizational transparency and user education.

4.3.2 Cultural Context and DEI Integration

Cultural context and organizational values significantly influence how AI is received and implemented. Participant 1 said that cultural norms shape how inclusivity is interpreted, warning that what is seen as inclusive in one country may be viewed negatively in another. Participants highlighted varying degrees of engagement with DEI across companies and regions. For instance, Participant 2 shared that recruitment often aligns more with team structure or client expectations than formal DEI targets. Similarly, Participant 3 showed little alignment with DEI principles, emphasizing candidate quality over demographic representation.

In contrast, Participant 11 emphasized that DEI success through AI requires strong internal culture and leadership support: "It's about vision and governance, training, strategy, and engaging people regularly." This quote reinforces the idea that inclusive outcomes depend not just on the technology itself, but on the surrounding organizational framework and strategic commitment to diversity. Some participants described symbolic DEI initiatives that lacked substance. Participant 9 pointed out that inclusive hiring efforts often fail without building a real ecosystem of acceptance: "They hire because it's an initiative… but they fail to create an ecosystem of acceptance." This shows that without genuine cultural integration, DEI-driven AI recruitment may appear performative and fail to generate long-term changes. These perspectives underscore the importance of not only using AI for inclusive hiring but also embedding DEI into the organization's cultural foundation.

4.3.3 Training and Communication Gaps

A significant concern across interviews was the lack of employee training around AI tools. Many participants stressed that without proper education, even well-intentioned AI implementations might provoke resistance. Participant 6 explained that AI adoption can "be a danger" if employees do not know how to use the tools correctly. Participant 10 also noted that fears around job replacement stems largely from poor communication: "AI is a complimenting tool, not completely with replacement." Illustrating that clear messaging and signalling can reduce resistance and help employees see AI as a support mechanism rather than a threat. Participant 11 identified education and leadership messaging as key to AI integration: "It's not just about technology, it's training, strategy, and engaging people regularly." This comment shows the importance of a holistic implementation strategy where communication, leadership, and learning are as crucial as the technology itself.

Several participants advocated for ongoing workshops or internal hackathons to bridge knowledge gaps and encourage responsible AI use (e.g., P10). Across participants, it was clear that the perception of AI in recruitment is shaped by trust, transparency, and cultural alignment. While some organizations view AI as an efficiency enhancer, others struggle with employee concerns and insufficient integration with DEI values. Addressing these gaps through communication, training, and inclusive governance was seen as essential for sustainable adoption.

4.4 Risk Mitigation

The increased adoption of AI in recruitment brings not only opportunities for efficiency and fairness but also a set of significant risks. Participants across the study identified concerns ranging from data privacy and over-reliance on automation to the lack of explainability in AI decisions. The responses highlighted a strong consensus on the need for robust safeguards, transparent practices, and regulatory oversight.

4.4.1 AI Literacy and Responsible Use

One of the most consistent concerns raised was the lack of AI literacy among both recruiters and decision-makers. Participant 11 stressed that poor understanding of how AI systems operate can lead to improper usage and unintended consequences: "You can't use AI if you don't know how it works. There's a big education gap right now." This view was reinforced by Participant 6, who noted that employees may treat AI as a black box, thereby increasing the likelihood of errors or misplaced trust: "If you don't know how to use AI, it can be a danger for yourself." These comments tell us that without foundational understanding, employees may misuse AI tools or develop mistrust, making training an essential component of responsible implementation. Participants advocated for structured training and internal learning sessions to help users engage critically with AI tools rather than passively accepting their outputs. Building a foundation of literacy was seen not only as a best practice but as a prerequisite for ethical and effective AI use.

4.4.2 Governance and Explainable AI (XAI)

Explainability, or the ability to understand how and why AI makes a particular decision, was a key issue. Several participants emphasized that without it, AI-driven recruitment processes lack transparency and accountability. Participant 8 stressed the importance of maintaining a human-in-the-loop, especially in decisions that significantly impact candidates: “AI should not replace the human entirely. There has to be someone reviewing and understanding what the system is doing.” Emphasising the belief that human oversight is essential for interpreting AI decisions and ensuring that critical judgements, particularly those affecting people’s careers, are made with context and empathy. Participant 10 shared a similar concern, stating that while AI can assist in screening, it still cannot interpret complex behavioural cues: “AI would not be able to answer behavioural questions… human resource can.” This comment supports the idea that human intuition and contextual understanding are still indispensable in parts of the recruitment processes where emotional intelligence is required. Participant 7 added that many platforms now include guardrails and prompts to ensure that users are aware of potential biases or gaps: “They build in prompts that challenge the user... ‘Are you sure you want to make that decision?’ That helps avoid shortcuts.” Demonstrating how explainability features can actively encourage users to reflect on their choices and mitigate potential bias, thus supporting more ethical and deliberate decision-making. These insights reinforce the need for organizations to not only use AI responsibly but to implement governance structures that mandate explainability and support ethical decision-making.

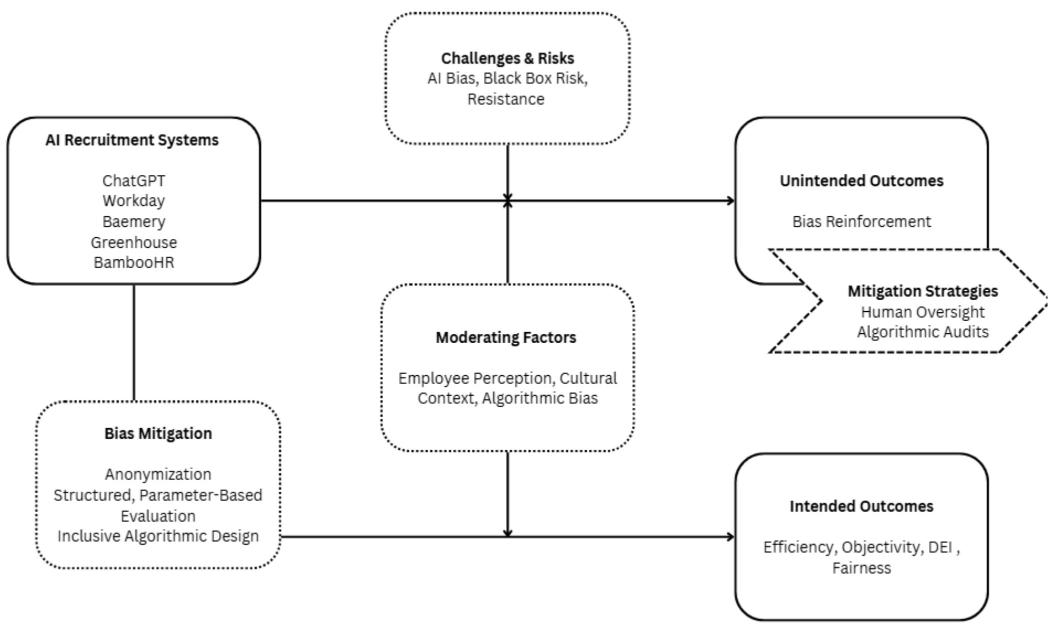
4.4.3 Regulation, Audits, and Compliance

Participants frequently cited external regulation and internal auditing as essential safeguards. Participant 11 advocated for an AI labelling system, similar to nutritional labels, which would help companies and users understand the scope, risks, and ethical standards of AI tools:
“There is no label today. We need ways to certify DI-optimized recruiting tools.” Signalling a desire for standardized frameworks that clarify whether AI tools meet Diversity & Inclusion and ethical benchmarks, helping organizations make more informed and responsible decision. The General Data Protection Regulation (GDPR) and the European Union AI Act were referenced as critical frameworks that organizations must align with. Participant 7 emphasized that compliance was not just a legal requirement but a trust-building measure. They noted that users are more likely to accept AI tools when they are confident those tools meet legal and ethical standards. In essence,

they suggested that regulatory compliance gives stakeholders the confidence to engage with AI systems more openly. Participant 8 recommended regular audits, transparent documentation, and ongoing monitoring to ensure accountability. Reinforcing the need for continuous oversight to catch potential issues early, and to maintain ethical standards as AI tools evolve. Participant 10 added that strong protocols are needed to avoid issues such as data breaches and biased automation: "We have witnessed a lot of hacking incidences… strong protocols are needed." Discussing the security risks inherent in AI adoption and the need for technical safeguards. Together, these findings point to a broad consensus: AI tools must be subject to formal review mechanisms, with vendors held accountable for ethical implementation and ongoing transparency. Across all interviews, risk mitigation emerged as both a technical and cultural challenge. While AI offers significant benefits, the absence of clear understanding, governance, and regulation could lead to serious ethical and operational issues. Ensuring that users are educated, systems are explainable, and policies are in place for oversight and compliance was seen as necessary for responsible AI integration.

4.5 Revised Theoretical Framework

The initial theoretical framework was revised based on the findings of this qualitative research.



4.1 Revised Theoretical Framework

5. Discussion and Conclusion

This chapter synthesizes the findings presented in Chapter 4 and connects them to the broader academic literature and the study's research questions. It reflects on how AI technologies are transforming recruitment in multinational enterprises (MNEs), particularly with respect to bias mitigation, employee perceptions, and risk management. This chapter is organized in the four themes' established in the analysis: 5.1 AI Tools in Recruitment, 5.2 Bias Mitigation, 5.3 Employee Perception and Cultural Context, and 5.4 Risk Mitigation, followed by the overall conclusion and limitations. It concludes with a critical reflection on the implications, limitations, and possible directions for future research.

5.1 AI Tools in Recruitment

AI is no longer a futuristic concept in recruitment; it is an operational reality with varying levels of integration across organizations. From ChatGPT-assisted communication to fully automated workflows using Beamery or Workday, participants described a wide spectrum of AI sophistication-levels. This aligns with literature that discussed a shift from early keyword-based filtering toward predictive and contextual hiring solutions using NLP and machine learning (Devaraju, 2022; Abdul, 2020).

The study confirms that efficiency, scalability, and personalization are core benefits of AI integration, relating to the findings by Madanchian (2024) and Maree (2018). Yet, the variation in AI-adoption reveals an important insight, which is that AI's effectiveness is not merely technological, but dependent on strategic implementation and user capability (Amershi, 2019). For instance, while Participant 4 described highly personalised, automated recruitment pipelines, others such as Participant 1 used AI in basic ways, such as simple checking grammar. This reinforces the role of human agency in prompting, configuring, and supervising AI, which suggests that the value derived from AI depends largely on how humans choose to interact with it.

Moreover, participants pointed out the challenge of balancing automation with human judgement. Participants warned that over-reliance on generic tools such as ChatGPT may strip recruitment of context and judgment, a concern also raised in literature (Winick, 2018; Grimmelikhuijsen, 2023). Therefore, AI should be seen not as a replacement, but a decision-support system that supports and strengthens human decision-making when used thoughtfully.

5.2 Bias Mitigation

Participants gave a balanced view of AI's potentials and challenges in bias mitigation. There was agreement that structured AI screening, anonymized CV reviews, and standardized evaluations can reduce human bias in early hiring stages. These mechanisms align with what research recommends, showing us how AI can help reduce human biases such as favouring people similar to ourselves or focusing solely on information that confirm what we already believe (confirmation bias) (Beattie, 2011; Chen, 2023).

Participant 11's reference to a military case, where AI outperformed human supervisors in promoting qualified women, serves as a compelling example of this corrective potential**.** However, multiple respondents cautioned that bias can be subtly incorporated in data, prompts, or poorly designed algorithms, reinforcing concerns by Albaroudi et al. (2024) and Dastin (2018). For instance, if historical hiring data tends to favour male or Eurocentric traits, AI will likely replicate those biases unless actively corrected.

A crucial insight here, is that AI itself is not inherently neutral. Its bias-mitigating potential relies on careful input design, continuous auditing, and transparent oversight**,** a view validated across literature (Rai, 2020; Pillai, 2024). Several participants advocated for hybrid models, where humans remain involved for critical stages of decision-making. This reflects a growing agreement that fairness in AI hiring is achieved not through automation alone, but through responsible co-usage by informed humans. Additionally, the article "Transitioning to Human Interaction with AI Systems" does emphasize the necessity of human involvement in AI usage. It argues that AI systems must be designed with human-centred principles to ensure they align with user needs and ethical considerations (Xu, 2023).

5.3 Employee Perception and Cultural Context

Employee perception emerged as a significant enabler, or barrier, to AI adoption. Trust, in particular, was shaped by transparency, communication, and demonstrated outcomes. Participants noted that scepticism often stems not from the AI tool itself but from a lack of clarity about its function and implications. This aligns with findings by Bankins (2022) and Bhargava et al. (2020), that emphasise that perception is often influenced by how AI is introduced, explained, and contextualized. Additionally, the findings align with the concept of Explainable AI (XAI). By making the decision-making processes of AI tools more transparent and understandable, XAI can help reduce distrust and promote fairness. When recruiters and employees can interpret why certain candidates are recommended or screened out, it mitigates the “black box” effect and fosters greater acceptance of AI outcomes (Rai, 2020; Dwivedi, 2023)

Organizational culture plays a moderating role in AI acceptance. Some companies integrate AI into strong DEI-oriented frameworks, using it to reinforce inclusive hiring (e.g., Participant 11), while others adopt AI practically, where choices are driven by client demands or team structure rather than a companies’ instinctive motivation (e.g., Participant 2). This supports Lichtenthaler’s (2020) conclusion that acceptance varies widely by context and is shaped by how well AI aligns with organizational values and communication strategies.

Training gaps were a reoccurring issue. Participants noted that poor understanding increases job displacement fears, with several advocating for workshops, internal hackathons, and leadership messaging to bridge the divide. As Akansha Mer (2023) and Lee (2018) argue, AI is more likely to be embraced when it supports, rather than threatens, human roles. When implemented ethically, with education, clarity, and feedback loops, AI can enhance engagement and inclusion.

5.4 Risk Mitigation

While the upside of AI in recruitment is considerable, so are the risks. Participants identified three primary areas of concern: misuse due to low literacy, lack of explainability, and poor regulatory alignment.

AI literacy was universally cited as a gap, among both recruiters and decision-makers. Confirming the research by Dwivedi (2023), several participants argued that ethical AI usage begins with understanding its limitations and strengths. Blind trust in AI outputs can create new risks (Janssen, 2022), including poor hires or legal liabilities.

Several participants emphasized the need for human governance and oversight in AI-driven recruitment, agreeing with the hybrid human-AI systems, to ensure fairness and accountability. This aligns with findings by Köchling et al. (2021), who argue that maintaining a human-in-the-loop is essential for interpreting candidate behaviour and mitigating algorithmic bias.

Explainability was another recurring theme. Without transparency into how decisions are made, participants feared that both internal stakeholders and candidates would lose confidence in AI systems. Literature on explainable AI (Rai, 2020; Li, 2022) supports this, stating that decision-tree models or post-hoc interpretability mechanisms are critical for fair and accountable outcomes.

On regulation and compliance, the study confirms that MNEs operate in a fragmented legal landscape, as discussed in Chapter 2. From GDPR to New York's AEDT Law, participants acknowledged the need to balance technological innovation with adherence to local data laws. The call for standardized "AI labels" (Participant 11) aligns with Zuiderveen Borgesius (2018) and PDPC (2023), who advocate for global standards in ethical AI governance.

5.5 Conclusion

This study contributes to a more refined understanding on how AI technologies affect recruitment in multinational organizations. It shows that while AI offers efficiency and the potential to reduce bias, its impact depends on organizational culture, employee perception, and regulatory caution. The human-AI interaction determines ethical outcomes. With key insights such as the conclusion that AI really is a tool, not a solution. Its effectiveness depends on thoughtful human use and ongoing supervision. Bias can be reduced but also reinforced. AI tools must be regularly audited and trained on inclusive, balanced data. Trust and culture matter. Transparent communication, DEI alignment, and education influence AI-acceptance.

Risks are real. Without governance, explainability, and regulation, AI systems can harm rather than help. Future research could further explore cross-cultural differences in AI perception, the role of AI in non-recruitment HR tasks, and longitudinal impacts of AI on workforce diversity and retention. For practitioners, the study recommends a dual focus on technical literacy and organizational readiness to ensure AI enhances, not sabotage, fairness, and effectiveness in recruitment.

The results of this research offer valuable insights for HR managers, DEI professionals, and organizational leaders that are seeking to implement AI-driven tools into their fields. A key takeaway is that AI alone is not a solution, its effectiveness is highly dependent on how well it is implemented, understood, and supervised. Many participants emphasized that, without proper user training and human oversight, AI systems may fail to deliver fair or desired outcomes. For managers, this shows the importance of investing not only in the technology itself but also in AI literacy among recruitment teams. Furthermore, the findings reveal that cultural context plays a significant role in how AI is perceived and accepted by employees of multinational companies. This suggests that decision-makers in multinational companies should strongly consider cultural contexts when wanting to introduce AI in decision-making processes. The findings also suggest the need for transparent communication and trust-building strategies, such as XAI, to address employee concerns about fairness, job security, and data use.

Furthermore, this study concludes that managers should make more informed decisions when selecting AI tools by demonstrating both the potential and limitations of AI in bias mitigation, designing governance frameworks, or aligning with AI-regulations such as GDPR or the EU AI Act. Lastly, this research supports a more ethical and effective use of AI in recruitment, one that considers both technological capabilities and human interference.

Though this study refers to AI tools in recruitment, it is important to note that these tools vary in how they work, what tasks they support, and how transparent their decisions are. And although the focus here is on recruitment, the findings apply more broadly. Whether used for resume screening, candidate matching, writing job descriptions, or communicating with applicants, all AI tools can carry risks, especially when trained on historical data as they may enforce stereotypes or reflect biased practices. This includes general-purpose tools such as ChatGPT or Copilot, as well as specialised platforms such as Workday or Greenhouse. Consequently, the need for transparency, inclusive data, and human oversight applies across the full spectrum of AI applications in HR.

While the primary focus of this study is on current applications and perceptions of AI in recruitment, several participants also reflected on its future potential and challenges. Most expect that a significant portion of organizations will adopt AI technologies in the near future, not only to improve efficiency in recruitment but also to support internal communication, workforce planning, and candidate engagement. However, the success of such developments depends on how responsibly these tools are going to be implemented. Continuous oversight, ethical safeguards, and investment in user/employee training remain essential to ensure that AI enhances fairness, efficiency, and effectiveness in HR-practices, rather than threaten these incentives.

5.6 Limitations and Future Considerations

This study generated insights into the role of AI in recruitment and diversity practices within multinational organizations, yet several limitations must be acknowledged.

First, the research is based on a qualitative design involving semi-structured interviews with 11 participants. Though this method allows for rich, in-depth exploration, it may still limit the generalizability of the findings. The sample, though diverse in roles and regions, may not capture the full range of organizational practices or various technological levels across industries. Future studies may benefit from incorporating a larger and more representative sample, while potentially even incorporating triangulation efforts through mixed method approaches that combine qualitative interviews with empirical findings.

Second, the study reflects a cross-sectional view of AI adoption, offering a snapshot of current practices and perceptions. However, AI technologies and organizational responses evolve rapidly. Longitudinal studies could help track how attitudes, usage patterns, and DEI outcomes shift over time as AI systems mature, and regulatory landscapes evolve. Most participants stated that with the speedy evolution of AI tools, there is a great chance that results will vary if the study would be conducted in 5 or even 1 year.

Third, while the sample included participants from diverse cultural backgrounds, including Dutch, Indian, Slovakian, Polish, French, and English participants, the study approached cultural diversity primarily through participants' individual reflections rather than systematic cross-cultural comparison. As such, cultural influences were explored in a contextual and anecdotal manner, without drawing structured contrasts between specific national or regional norms. Future studies could benefit from a comparative case study design that deliberately samples participants across clearly defined cultural dimensions (e.g., power distance, individualism vs. collectivism, or regulatory environments). This kind of approach would allow for a clearer understanding of how cultural differences actually shape trust in AI, perceptions of fairness, and the acceptance of automated decision-making. This is particularly relevant for multinational organizations that implement AI recruitment tools globally, as localised differences in culture, legal constraints, and ethical norms, may significantly affect the effectiveness and perceived legitimacy of these systems. A structured cross-cultural comparison could therefore enhance the generalizability of findings and help develop AI strategies that are better tailored to varying cultural contexts.

Fourth, this research did not directly evaluate the technical performance of the AI tools mentioned (e.g., Workday, Beamery, ChatGPT) nor access proprietary algorithms. As a result, conclusions regarding bias mitigation or ethical risks are based on user perceptions rather than empirical audits of the systems themselves. Future studies could integrate technical evaluations for example, fairness audits, model explainability tests, or bias detection tools, to complement human-centred insights. Finally, the research primarily focused on recruiters, DEI managers, and HR professionals. Including additional stakeholders such as candidates, AI developers, or legal and compliance officers could generate an even more comprehensive view on the ethical, operational, and social implications of AI-driven recruitment.

With regard to these limitations, future research should aim to explore the dynamic between AI systems and human decision-making across diverse contexts. As AI is increasingly integrated into HR practices, it is important to assess not only its technical capabilities but also its impact on society, ethic, and culture.

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Appendices

Appendix 1, Themes: AI Tools in Recruitment & Bias Mitigation

	AI Tools in Recruitment	**Bias Mitigation**
Participant 1	Uses an AI language checker to ensure job postings are gender neutral. Participant noted: 'The AI checker helps us become aware of unconscious bias in our language.' Also discussed broader use of AI in recruitment screening, though with ethical concerns about tools such as ChatGPT.	Initiatives include removing reference letters and student evaluations due to proven bias. Actively use inclusive language in job ads, ensure gender-balanced shortlists, and avoid biased performance indicators.
Participant 2	Expressed scepticism about AI tools in recruitment. Concerned that reliance on specific keywords might cause loss of talent: "What if you just use... a different set of words. You would just again lose a talent." Currently uses ChatGPT mainly for grammar and wording when writing to candidates or posting vacancies.	Stressed the importance of addressing biases starting with hiring managers: "You need to work with the hiring manager... if they have some biases or... criteria that are like non functional." Shared experiences of recognizing and correcting personal biases during high-volume hiring: "...what if I didn't have this knowledge? What if I would just stop with these three candidates and would not take the interview of the 4th one? Then I would miss the talent."
Participant 3	Frequently uses ChatGPT for tasks such as CV screening, writing vacancy texts, and matching candidate profiles to job requirements. They found the tool helpful and accurate, noting that it assists in identifying strengths and weaknesses in candidate applications. They also observed that AI tools are	Emphasized prioritising candidate quality over demographic characteristics such as gender, ethnicity, or age. They were critical of diversity quotas, expressing concern that such measures might shift focus away from qualifications and lead to the exclusion of strong candidates. They also acknowledged the influence of personal bias, citing negative past experiences with candidates from a specific ethnic background.

	becoming more widely used among recruiters and significantly speed up the recruitment process.	
Participant 4	Participant 4 detailed a multi-level AI integration in recruitment, from CV screening and workflow automation to psychometric assessments and follow-up question prompts during interviews. "Once you have those 50 CVs... just give the box access to the tool... All you can do is start sending mails... everything will be personalized."	They emphasized structured, parameter-based AI systems to remove human bias. "When you have parameters, you cannot be biased... that's where it helps to remove bias on the first level of recruitment." They also discussed how automated systems track recruiter behaviour to prevent discriminatory shortcuts.
Participant 5	Participant 5 noted that current AI use is still limited in most companies, mainly applied for: Keyword filtering in CVs Anonymizing applications to hide names/photos and reduce bias Internal mobility systems that guide employees on skill development toward future roles.	Anonymization was highlighted as a useful method to remove bias. Stressed that AI systems must be carefully trained and continuously tested, warning that bias can still enter these models if they are not regularly verified and updated. Warned that poor implementation or shortcuts could reintroduce bias or make it harder to detect.

Participant 6	Described several AI functionalities in recruitment: Resume screening by a robot that selects the best candidate. Qualification testing and competency/culture matching. Interview scheduling and virtual assistance. Believes AI increases efficiency: “AI uses many systems… the robot is to selection the best resume of this candidate.	Strongly believes AI can improve fairness in hiring: “If they are the same candidates and have the same qualifications, AI is comparative by these candidates and have the best resume that needed the company.” AI focuses on qualifications, experience, and background, ignoring race, religion, gender, or age. Warned that companies could still misuse AI: “The AI chooses this age, this limit for the ages... maybe that candidate then have after 30 age old, that’s excellent to the AI.” Acknowledges that AI could be programmed to discriminate, depending on company instructions.
Participant 7	Participant 7 explained that many HR professionals use general productivity tools like ChatGPT and Microsoft Co-pilot to support daily tasks. They also mentioned the use of more advanced systems, such as Beamery at ASML, where AI is integrated into the recruitment process. For example, filters are applied during CV screening based on criteria like years of experience and educational level.	Acknowledged that bias is a real risk in AI-driven hiring, especially when filters are based on sensitive attributes such as names, age, or nationality. They emphasized the importance of incorporating guardrails and system prompts that help users reflect on potentially biased inputs. Additionally, they suggested using AI tools to assess recruiters themselves for implicit bias as part of a more accountable hiring process.
Participant 8	Participant 8 works with both developers and companies purchasing AI tools. Highlighted platforms such as Workday that match candidates to job descriptions and assign fit scores. Described tools that:	Warned that bias is very difficult to eliminate from AI tools due to human influence and flawed training data. Shared experience: “One recruiter said, ‘I like candidates who play chess,’ and biased the system accordingly.” Emphasized importance of: Regular auditing (e.g., using the “80% rule”).

	Scrape data from LinkedIn and social media. Conduct CV screening and even full interviews (avatar agents). Include chatbots that automate candidate outreach. Concern: “If your LinkedIn profile is not visible, you will be automatically excluded... That’s discrimination against people who value privacy.”	Training recruiters to write unbiased prompts and descriptions. Involving lawyers and compliance experts in development. On anonymization: “AI should be able to filter identifying data, but most developers don’t consider this due to lack of resources or awareness.”
Participant 9	Has 10+ years of experience using AI tools such as chatbots, RPA (Robotic Process Automation), IQ bots, and HRMS platforms (e.g., Workday, SuccessFactors, BambooHR). Described AI tools capable of: Sourcing, screening, interviewing, and onboarding candidates. End-to-end HR management, including performance and separation modules. “There are bots which can log into job portals and source 100 profiles in 10 seconds.” AI improves efficiency but must be used with the right inputs: “Technologies never give you deliverables unless you give them the right input.”	Believes bias originates in human behaviour, not AI itself: “Biasness lies within us… technology doesn’t have anything.” AI can support D&I initiatives if programmed and used correctly (e.g., auto-removing gendered language from job descriptions). “Tools like SuccessFactors or Workday auto-eliminate biased keywords in JDs.” Emphasized the role of refined algorithms and access to diverse hiring communities (e.g., LGBTQ forums in Africa, Dubai, etc.). “With the help of technology, you can connect with D&I communities and create visibility.”

Participant 10	Uses ChatGPT, Gemini, Greenhouse, and integrated platforms in daily recruitment tasks. Applies AI to: Understand unfamiliar roles (e.g., Salesforce Architect). Support employer branding. Aid in resume sourcing and role analysis. Participated in internal AI hackathons to test new recruitment tools. "I took their help on my daily recruitment task, as in resume resourcing… it was a great help."	Believes AI is generally unbiased, but susceptible to human manipulation: "AI is not biased… but yeah, if you want, you can make it biased." Uses platforms such as Greenhouse, which notifies if resume rejections are too quick: "There's a trigger notification… 'try to make your decision unbiased.'" Acknowledges that bias in job descriptions (e.g., using masculine words) could still influence AI outcomes. Sees potential for AI to help reduce bias, but not universally applied yet: "AI is really helping to keep your pipeline unbiased."
Participant 11	Recognizes AI as a "double-edged opportunity"—offering both efficiency and risk. Emphasized use of AI for: Expanding talent pools Tracking diversity metrics Automated CV parsing, including image data such as photos Critiqued recruiters who rely on public AI models (e.g., ChatGPT) for screening: "Many recruiting firms are using the public models of ChatGPT... they take attachments and ask the AI to do the job they should be doing as humans." Encouraged moving toward	Highlighted that bias often lies in input data and human interpretation, not AI itself. Advocated for: Training data to reduce bias Human supervision of AI outputs Audits of vendors for DEI accountability Gave a powerful example of AI outperforming humans in gender-neutral promotion predictions in a French military project: "The AI would have promoted more women. The gap was 8%—those women were not promoted by human supervisors."

	specialized recruitment AI vendors with more inclusive setups.	

	Employee Perception & Cultural Context	**Risk Mitigation**
Participant 1	Emphasized cultural differences affecting perceptions of inclusiveness. Noted challenges due to varying definitions of inclusiveness across cultures: 'Even when you're being inclusive by Dutch standards, it might be offensive to someone from a high-context culture.	Acknowledged risks of AI misuse and cultural bias in tools. Stressed importance of human involvement, data management, and tailoring tools to the European context. Also expressed need for better analytics tools to evaluate promotion fairness and representation.
Participant 2	Emphasized the need for representation of dominant groups in DEI efforts to prevent feelings of exclusion: "If they're not represented in these initiatives... They might feel, you know, threatened." Reflected on how DEI development may face setbacks influenced by political trends, especially from the U.S., but ultimately sees it as progress over time.	Warned about risks of over-relying on AI, especially in creative fields: "AI is not... possible for AI to recreate the same... aesthetic preferences." Believes DEI is more practical in well-established companies with sufficient resources: "It seems that DEI is more for companies that are well established and they have like... time and effort for that."
Participant 3	Recruitment strategy aligns with team needs and client preferences, such as age balance or gender ratio. Has low engagement with DEI frameworks, stating the focus is on "internal qualities" and performance.	Participant 3 expressed scepticism about AI's role in promoting inclusivity, suggesting that current systems focus primarily on qualifications rather than diversity-related criteria. They also warned that AI tools may become increasingly essential but financially burdensome over time, drawing a comparison to the rising costs of platforms like LinkedIn.

Participant 4	Participant 4 recognized that employees may fear AI due to lack of knowledge and suggested trust-building via transparency and continuous training. "Companies should provide resources, people should use it... trust comes from knowledge."	They stressed that risk depends on leadership ethics and parameter-setting: "AI helps to achieve your objectives... if your objective is biased, AI will help that too unless controlled." Advocated for regulatory safeguards and experienced leadership to manage AI implementation safely.
Participant 5	Emphasised the need for transparency and a shared vision when implementing AI in recruitment. They argued that employees are more likely to trust and adopt AI tools when they clearly understand the purpose and direction. Additionally, they believed employees should experience the benefits of AI firsthand—such as freeing up time for more meaningful, human-centred work. They stressed that AI should not replace the human element entirely but instead work in symbiosis with HR professionals.	Identified key risks in AI-driven recruitment, such as unfair rejection of candidates without clear reasoning and the potential for unethical misuse. They emphasized the importance of transparency—advising organizations to clearly communicate how AI is used in the recruitment process. To ensure ethical and effective outcomes, they strongly advocated for continuous testing and monitoring of AI systems.
Participant 6	AI adoption may trigger fear among employees; companies need to build trust: “All the companies will be needed AI to succeed… but if you don’t know how to use AI, it can be a danger for yourself.” Emphasizes the need for training and information: “You should have a course to have a big information for how to use AI.”	Warns about ethical risks in AI deployment: Unfair rejections due to algorithmic decisions. Potential discrimination if AI is misused (e.g., filtering by gender, religion). Argues that humans are still needed, especially in early implementation stages: “Now there is a robot of interview… maybe in the future, all things the robot will do… but now human is still needed.” Recommends proper AI training, testing, and ethical programming.

Participant 7	Emphasized that transparency plays a significant role in building trust between employees and AI systems. They noted that when people understand what AI is and how it works, they are more likely to accept it. They also highlighted that acceptance of AI varies across contexts and is shaped by societal norms and regulatory frameworks, such as the AI EU Act and GDPR.	Warned that using AI without a clear understanding, such as providing poor prompts, can lead to low-quality or misleading outputs. They emphasized the need for thorough training and ensuring compliance with legal standards before implementing AI tools. Additionally, they cited real-world risks including politicized system responses, potential for discrimination, and a lack of explainability in AI decisions.
Participant 8	Strongly supported transparency to ease employee concerns and foster trust: "Explain how the tool works... that it will not replace people, but support them." Advocated for internal training sessions to help staff understand AI tools and reduce resistance: "Understanding how these tools work is the most important thing."	Described numerous risks: Exclusion of qualified candidates due to weak online profiles. Lack of human oversight, especially when automation is prioritised for speed. Developer-business disconnect: developers aim to scale fast, neglecting ethics. Mitigation strategies: Maintain human-in-the-loop, ideally at multiple steps. Keep detailed documentation of AI processes and user complaints. Ensure compliance with the AI Act and GDPR. "The most important thing is regular auditing and human oversight at every point—or at least at key checkpoints."

Participant 9	AI is useful, but human acceptance is crucial: “Acceptance is everything… Adoption is very easy. Adapting is very difficult.” Cited IBM’s efforts to create inclusive physical workspaces for LGBTQ employees. Warned that without an ecosystem of inclusion, tech-based diversity efforts will fail: “They hire because it’s an initiative… but they fail to create an ecosystem of acceptance.”	AI's success hinges on ethical implementation, oversight, and data security. Warned against over-dependence and lack of data control. “If you lose control of your data, you lose control of everything.” Advocated for balance and boundaries in AI use: “Don't have complete dependency on any of the technologies.” Rejected the idea that AI will replace humans: “Technology will make you better, not replace you—unless you’re rigid and don’t adapt.”
Participant 10	Acknowledges that employees fear AI might replace them, especially in tech-reliant companies. Believes AI should be viewed as a support tool, not a replacement: “AI is a complimenting tool, not completely with replacement.” Emphasizes upskilling and adaptability for long-term job relevance: “To stay in your job—learn.”	Warns of risks in full automation of hiring without human input:\ “AI would not be able to answer behavioural questions… human resource can.” Advocates for human oversight and operation of AI tools: “Every organization might replace a recruiter, but they need someone to operate the AI.” Concerned about data privacy and hacking: “We have witnessed a lot of hacking incidences… strong protocols are needed.” Believes transparency is valuable, but must be balanced with security: “Privacy and transparency is the concern.”

Participant 11	Stressed importance of trust, leadership, and communication in AI adoption: “Trust is essential… You build trust by showing results—efficiency, capability, inclusive outcomes.” Emphasized internal culture and C-level endorsement to normalize AI use in recruitment: “It’s about vision and governance—training, strategy, and engaging people regularly.”	Major risks identified: Lack of AI literacy and education Poorly trained or unsupervised models Over-reliance on emotion/face analysis (cited the Higherview case) “Once you reintroduce the human, you potentially reintroduce new bias. But it’s still better than letting AI work unsupervised.” Recommended: Internal & external audits Explainable AI with clear scoring and transparent logic Vendor accountability Called for AI governance and labelling systems for ethical recruiting: “There’s no label today. We need ways to certify DI-optimized recruiting tools.”

Appendix 3, Interview Protocol – English

1. Leveraging AI to Identify and Mitigate Biases in Recruitment

- From your experience, what are the most effective AI tools currently used to reduce bias in recruitment?
- How does AI identify biased language or criteria in job descriptions or candidate screening processes?
- Have you encountered any cases where AI tools succeeded in mitigating bias where traditional methods failed? Could you elaborate?

2. Enhancing Diversity through AI in Multinational Organizations

- In what ways can AI actively promote diversity in hiring across different regions or cultural contexts?
- How do you see AI balancing the need for diversity with the need for role-specific qualifications?
- Have you observed any measurable improvements in diversity metrics after implementing AI?

3. Employee Perception and Trust in AI Systems

- How important is employee perception and trust when introducing AI into recruitment systems?
- What are the most common concerns raised by employees regarding AI in recruitment—especially in multicultural settings?
- How can organizations increase transparency and build trust in AI recruitment tools?

4. Risks and Ethical Considerations

- In your view, what are the most significant risks of relying on AI in recruitment?
- Can you provide examples of how AI tools have unintentionally reinforced existing biases?
- What kind of oversight or human intervention do you think is necessary to prevent discriminatory outcomes?

5. Cultural Contexts and Moderating Factors

- How do cultural differences impact how AI recruitment tools are perceived or received by employees?
- Have you seen cases where the same AI system worked well in one country but faced resistance or failed in another?
- What strategies can multinational companies adopt to ensure cultural sensitivity in AI implementation?

6. Future Outlook

- How do you see the role of AI in recruitment evolving over the next five years?
- Do you believe we will ever reach a point where AI can completely replace human judgment in hiring decisions? Why or why not?

Wrap-Up Questions

- If you had to advise a multinational just beginning to implement AI in their hiring process, what would be your top three tips?
- What is one misconception people often have about AI in recruitment?

Appendix 4, Interview protocol – Dutch

1. AI inzetten om bias in werving te identificeren en te verminderen

- Wat zijn volgens u de meest effectieve AI-tools om bias in werving te verminderen?
- Hoe herkent AI bevooroordeelde taal of criteria in vacatureteksten of bij het screenen van kandidaten?
- Heeft u voorbeelden waarbij AI succesvol bias wist te verminderen waar traditionele methodes dat niet konden? Kunt u dat toelichten?

2. Diversiteit bevorderen via AI in multinationale organisaties

- Op welke manieren kan AI bijdragen aan meer diversiteit in de werving, vooral in verschillende regio's of culturele contexten?
- Hoe ziet u de balans tussen diversiteitsdoelen en functie-eisen bij het gebruik van AI?
- Heeft u verbeteringen in diversiteitsstatistieken gezien na de implementatie van AI?

3. Medewerker perceptie en vertrouwen in AI-systemen

- Hoe belangrijk is de perceptie en het vertrouwen van medewerkers bij de introductie van AI in het wervingsproces?
- Wat zijn de meest voorkomende zorgen van medewerkers met betrekking tot AI in werving, vooral in multiculturele omgevingen?
- Hoe kunnen organisaties transparantie creëren en vertrouwen opbouwen in AI-wervingstools?

4. Risico's en ethische overwegingen

- Wat zijn volgens u de grootste risico's van het gebruik van AI in werving?
- Kunt u voorbeelden geven van situaties waarin AI onbedoeld bestaande biases heeft versterkt?
- Welke vorm van toezicht of menselijke tussenkomst is volgens u nodig om discriminatie te voorkomen?

5. Culturele context en beïnvloedende factoren

- Hoe beïnvloeden culturele verschillen de perceptie en acceptatie van AI-wervingstools?
- Kent u voorbeelden waarbij een AI-systeem goed werkte in het ene land, maar weerstand of problemen ondervond in een ander land?
- Welke strategieën kunnen multinationals toepassen om culturele gevoeligheid te waarborgen bij de implementatie van AI?

6. Toekomstvisie

- Hoe ziet u de rol van AI in recruitment zich ontwikkelen in de komende vijf jaar?

- Denkt u dat AI ooit volledig het menselijk oordeel in werving kan vervangen? Waarom wel of niet?

Afsluitende vragen

- Als u een multinational zou adviseren die AI in hun wervingsproces wil introduceren, wat zouden uw drie belangrijkste tips zijn?
- Wat is een veelvoorkomend misverstand over AI in recruitment?

Appendix 5, LinkedIn approach message

"Hi!

My name is Fatimina Ahmed, and I am a master's student in International Management at Tilburg University. I am conducting research for my thesis on how AI is being leveraged to promote Diversity, Equity, and Inclusion (DEI) in multinational organizations, particularly in recruitment and employee engagement.

I am looking to interview HR professionals, DEI managers, employees, and AI developers who have experience with or insights into AI-driven HR tools. Your expertise would be valuable in understanding the impact of AI on mitigating biases, fostering diversity, and improving employee engagement.

What to expect:

• A 45-minute virtual interview at a time convenient for you. [NL/ENG]

• Questions will focus on your experience with AI tools in HR, their effectiveness in DEI efforts, and potential challenges.

• Your responses will be anonymized and used solely for academic research.

If you are open to participating, or if you know someone who might be a good fit, please let me know. I would greatly appreciate the opportunity to learn from your insights!

Feel free to reply here or reach out via LinkedIn or email at f.ahmed@tilburguniversity.edu.

Looking forward to your response!

Best regards,

Fatimina Ahmed"