BI

WISEflow
Europe/Oslo(CEST)
30 Jun 2023

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	**Annika Maren Haight og Elizabeth Solveig Johnson**

Informasjon fra deltaker

Tittel *:	Coping with Ethical Challenges in AI Recruiting
Navn på veileder *:	Elizabeth Solberg

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	39
Andre medlemmer i gruppen:	

Master Thesis
BI Norwegian Business School

Coping with Ethical Challenges in AI Recruiting

Examination code and name:

GRA 19703 – Master Thesis

Hand-in date:

03.07.2023

Campus:

Oslo

Supervisor:

Elizabeth Solberg

Study Program:

Master of Science in Leadership and Organizational Psychology

Acknowledgements

First and foremost, we wish to express our deepest gratitude to our supervisor, Adjunct Associate Professor Elizabeth Solberg. Her guidance, attention to detail, and consistent support throughout this process has been extramental.

Additionally, we extend a big thank you to our final 15 participants who generously dedicated their time and expertise. Their active involvement and insightful contributions significantly contributed to the depth of our findings.

As a final note, we wish to acknowledge the great partnership between us as partners. The experience of working together has been uplifting, enriching, and an honor. Memories and friendships have been made.

Oslo, 03.07.2023

Elizabeth Johnson

Annika Haight

Abstract

This paper examines the ethical challenges HR practitioners face when integrating AI recruiting tools into their selection processes. The study identifies key areas of ethical concern, including privacy, AI performance, and transparency and accountability. To address these concerns, the paper introduces the Coping Strategies for AI Recruiting Maturity Model (CS for AIR-MM), which offers a comprehensive framework for managing ethical AI recruiting practices. By utilizing this model, organizations can assess their AI-driven recruitment practices, identify areas in need for improvement, and implement measures to uphold ethical standards. Accordingly, the CS for AIR-MM acts as a valuable tool for HR practitioners to facilitate ethical AI recruiting practices.

1.0 Introduction

1.1 Case Identification

The term AI recruiting applies to any process that utilizes artificial intelligence to assist organizations in recruiting and selecting candidates for employment (Hunkenschroer & Luetge, 2022). AI is commonly used in recruiting when referring to technologies that enable computers to perform cognitive tasks typically performed by humans (Tambe et al., 2019).

According to research and AI vendors, using AI tools in recruitment can provide significantly more accurate and efficient decisions when properly designed and tested (Charlwood & Guenole, 2022; Langer & Landers, 2021). Through its use, time-consuming tasks such as resume screening, email communication, and interview scheduling could potentially be eliminated from human recruiters' responsibilities (Ore & Sposato, 2021). By leveraging CV assessment in conjunction with application tracking systems, more advanced AI systems have the potential to effectively identify and shortlist the most suitable candidates for further consideration (Hunkenschroer & Luetge, 2022). AI may also facilitate better employee performance evaluations, which can be used to determine the most qualified candidates, as well as those to promote (Charlwood & Guenole, 2022). Further, AI technologies can potentially be used to support candidate sourcing by providing a deeper understanding of talent acquisition requirements (Ore & Sposato, 2021). These core recruitment activities are not only easily handled by AI technologies but may also be performed at a speed that exceeds human capacities (Black & van Esch, 2020). By reducing administrative tasks, AI can improve labor productivity by freeing up the time of human recruiters to concentrate on more complex HR tasks (Ore & Sposato, 2021). According to AI vendors, automated recruiting systems offer enhanced accuracy and efficiency in decision-making, while also reducing bias and promoting fairness. By eliminating reliance on human intuitions or heuristics unrelated to job performance, these systems aim to provide more objective assessments (Charlwood & Guenole, 2022; Hunkenschroer & Luetge, 2022).

Yet, while the claims surrounding AI systems may seem promising, several researchers have raised concerns regarding the dependence of these systems on the quality and biases present within the data they receive (Cho et al., 2023). AI systems are not immune to bias, and they may even replicate or amplify existing biases (Ore

& Sposato, 2021). Further, automated systems may lack transparency, making it difficult to explain the decisions they make (Budhwar et al., 2022). This can lead to a lack of accountability and potential discrimination against certain demographics, making AI recruiting a potentially risky endeavor (Black & van Esch, 2020; Budhwar et al., 2022).

For instance, in 2018, Amazon discovered that its AI recruitment algorithms were flawed, resulting in biased and discriminatory behavior (Tambe et al., 2019). Amazon developed the algorithm based on past job performance data from its predominantly white male workforce (Hunkenschroer & Luetge, 2022). Consequently, the AI tool favored white male applicants, resulting in higher scores for them, while automatically dismissing candidates with attributes commonly associated with women (Charlwood & Guenole, 2021; Tambe et al., 2019).

Although there has been a significant surge in AI recruiting research in recent years, a comprehensive ethical understanding of the recruitment process as a growing AI application is still lacking (Hunkenschroer & Luetge, 2022). In particular, there appears to be limited literature describing how HR managers should cope with the ethical challenges managing inherent in AI recruitment. This is problematic given the substantial impact AI recruiting could have on people's lives and behaviors (Brendel et al., 2021).

This study will investigate different ethical concerns practitioners could have in using AI recruiting, especially during the selection process, and identifying coping strategies, as well as propose a maturity model for coping with these ethical concerns. The research question guiding our study is:

"How can HR practitioners cope with the ethical challenges posed by AI recruiting?"

To gather data for this study, the Delphi method will be employed (Hsu & Sandford, 2007). Accordingly, an exploratory study is the most appropriate research design, as the purpose is to clarify an understanding of a problem and to evaluate the phenomena from a new perspective (Edmonds & Kennedy 2017; Saunders et al., 2019).

This study will contribute to the research on AI recruiting in selection processes by filling the gap in the literature regarding the ethical challenges associated with AI recruiting and the strategies that can be used to cope with them.

Moreover, academics and practitioners will benefit from the maturity model developed in this study, as it can provide valuable guidance on how to apply AI technology while ensuring ethical recruitment practices. In addition, these findings will enable HR practitioners with a deeper understanding of ethical AI management, as it will provide them with the insight to make well-informed decisions to cope with challenges in practice. The results of this work may also open further research in the area and aid in the development of best practices for the ethical deployment of artificial intelligence.

2.0 Theory

2.1 Ethical concerns associated with AI recruiting

The current literature identifies four categories of ethical concerns that relate to the use of AI recruiting, namely privacy, performance of AI, transparency and accountability, and job concerns. By identifying these four categories of ethical concerns, the literature provides a comprehensive overview for understanding and addressing the ethical implications of AI recruiting.

2.1.1 Privacy Concerns

When using AI technologies, data is often collected by accumulating it from a variety of sources (Kaplan, 2022). AI tools in recruitment thereby depend on data provided by third parties and may collect information that is not relevant or is prohibited by data privacy regulations (Brendel et al., 2021). Privacy issues are therefore a growing concern in the context of automated decision-making (Hunkenschroer & Luetge, 2022; Langer & Landers, 2021). Likewise, Budhwar et al. (2022) argue that since the nature of AI involves continuous learning through the collection of data, the method in which the data is stored further exposes users to privacy risks. It is also increasingly difficult to determine who owns data and how to address privacy concerns as AI applications evolve (Hunkenschroer & Luetge, 2022).

Furthermore, automated systems may access candidates' social media accounts to acquire further information (Tambe et al., 2019). AI recruiting tools may raise ethical concerns as they are capable of gathering and analyzing highly personal information about candidates, including their health status, personality traits, and sexual orientation, by scraping social media platforms (Hunkenschroer

& Luetge, 2022). This allows personal information to be used or shared without the knowledge or consent of the candidate, posing a serious privacy concern (Black & van Esch, 2020).

2.1.2 Performance of AI

Despite the fact that research suggests AI tools have less bias and are more objective than human recruiters, its performance may suggest otherwise (Black & van Esch, 2020; Ore & Sposato, 2021). AI has its limitations, as the technology may not always function as intended (Budhwar et al., 2022; Hunkenschroer & Luetge, 2022; Tambe et al., 2019). Since AI technologies are created by humans, there is a risk that human error can be built into the algorithm, despite well-intentioned and fair computing processes. Biased or non-representative data along with insufficient modeling procedures can further cause AI algorithms to be discriminatory (Ore & Sposato, 2021; Zhang et al., (2021).

Moreover, AI tools may unknowingly adopt biases by screening applicants based on qualities displayed by individuals in top positions within an organization (Black & van Esch, 2020). Data derived from past employment is likely to result in hiring algorithms that disproportionately seek out one group of individuals (Tambe et al., 2019). Specifically, this problem contributed to the biased results of the Amazon hiring algorithm (Charlwood & Guenole, 2022).

Unlike humans, AI bots can act unethically by chance. Besides design problems and learning issues, external factors also contribute to the likelihood of this happening (Brendel et al., 2021). Data inaccuracies can have a significant influence on the recruitment process. Moreover, existing literature suggests that AI enables companies to make more reliable decisions over time (Hunkenschroer & Luetge, 2022; Kaplan, 2022). AI-based assessment techniques promise to offer the advantage of providing a consistent assessment experience to all applicants, thereby enhancing the consistency of candidate evaluations (Leutner & Chamorro-Premuzic, 2018). Nevertheless, there is ongoing debate regarding the accuracy and validity of AI tools (Hunkenschroer & Luetge, 2022). Tambe et al. (2019) raise concerns about the potential for AI to exhibit variations in performance among individuals, leading to accuracy issues and hiring discrimination. Furthermore, the authors highlight the challenge of striking a balance between accuracy and addressing other ethical concerns in AI recruiting decision-making (Tambe et al., 2019).

Further, there have been questions about the technical robustness and validity of AI-driven assessment tools since the new AI tools have not been adequately scientifically validated in terms of their underlying parameters for measuring job performance (Hunkenschroer & Luetge, 2022).

2.1.3 Transparency and Accountability

Several issues related to transparency and accountability must be considered when using AI systems (Goretzko and Israel, 2022). When AI recruiting is involved, employers, employees, and candidates should communicate in an open and transparent manner, given the lack of transparency associated with AI recruiting (Budhwar et al., 2022; Gaudio, 2022). Accountability in AI-driven recruitment is a critical aspect closely tied to the need for transparency. Hunkenschroer and Luetge (2022) address the question of who should be held accountable when using AI in recruiting. They discuss whether the responsibility lies with the AI developers, the hiring managers, or the company engaging in AI recruiting itself. Moreover, the issue becomes more complex when organizations acquire the AI tool from an external third-party, who may be reluctant or unwilling to disclose details of the algorithm used (Sánchez-Monedero et al., 2020; Tambe et al., 2019). In the opinion of Lin et al. (2020), it is evident that the AI tool itself cannot be held accountable. Ultimately, a human must be the one who is responsible. However, AI recruitment may lead to a muddled understanding of responsibilities and accountabilities, posing an ethical concern that must be addressed (Hunkenschroer & Luetge, 2022).

Researchers have expressed concern over the matter of trust, as it has been repeatedly noted that lack of trust and ethical dimensions of AI in the context of data information (Goretzko & Israel, 2022; Gaudio, 2022). Goretzko and Israel (2022), argue that the human mind is incapable of tracing the steps taken to reach specific conclusions when using AI technologies, emphasizing the importance of transparency and accountability when using AI recruiting in selection processes. Additionally, Budhwar et al. (2022) identifies several negative implications of utilizing AI recruiting. They state that services involved in highly emotional complexities call for emotional sincerity, which in most cases humans are more capable of conveying (Budhwar et al., 2022).

2.1.4 Job Concerns

Black and van Esch (2020) assert that recruitment professionals could perceive AI tools as a threat to their employment. Lee (2017) estimates that AI will automate and subsequently replace 40 percent of jobs by 2030, including many white-collar positions, further highlighting the potential threat to human employment (Loebbecke et al., 2020). Moreover, some publications state that employees may have further apprehensions about AI recruiting tools when they do not understand how the technologies may assist them in providing HR management services (Budhwar et al., 2022).

Additionally, AI recruiting technologies may enable constant surveillance at work, as it is designed to collect and store data continuously (Charlwood & Guenole, 2021). This practice can lead to an oppressive and intimidating work environment, where employees feel like they are constantly being watched and judged (Charlwood & Guenole, 2022).

2.2 Theoretical Framework

The rapid development of disruptive technologies such as AI recruiting brings forth a new and demanding dimension to the workplace. Given the growing ethical concerns associated with AI recruiting, it is essential to have the ability to effectively cope with these challenges. Developing coping strategies becomes imperative for navigating the ethical landscape of AI recruiting.

Coping is a multifaceted concept that plays a crucial role in managing and responding to stressful situations. Through their examination of various definitions, Latack and Havlovic (1992) suggest that coping is an essential component of the dynamic interplay between individuals and their environment. This interaction occurs when the individual perceives a situation as stressful, which can manifest as harm, threat, or challenge (Lazarus & Folkman, 1980). To encompass coping strategies, an inclusive and comprehensive definition of coping is adopted, as proposed by Folkman and Lazarus (1980). According to their definition, coping refers to the ongoing and adaptive cognitive and behavioral efforts individuals undertake to manage the demands arising from internal and external transactions that surpass or strain their available resources. This expansive definition allows for the inclusion of diverse coping strategies, whether they involve internal aspects such as emotional reactions or external factors such as the situation itself (Latack & Havlovic 1992).

Kahn et al. (1964) proposed a classification that encompasses two categories of coping strategies: *Class I Coping*, which involves addressing task-related situations and problem-solving, and *Class II Coping*, which involves managing emotions or anxiety reactions (Latack & Havlovic, 1992). Further research by Lazarus and Folkman (1984) popularized the terms *problem-focused coping* and *emotion-focused coping.* Problem-focused coping is defined as attempts to modify the person-environment interaction, while emotion-focused coping is characterized by attempts to regulate emotions (Latack & Havlovic, 1992).

Utilizing Latack and Havlovic's (1992) *Evaluative Framework Applied to Coping Measures*, we can delve into diverse coping strategies available to HR practitioners when confronted with ethical dilemmas arising from AI recruiting in the selection process. This framework encompasses problem-focused coping and emotion-focused coping as two key coping mechanisms to consider. In the context of our study, the most relevant response will be problem focused coping, as our conceptual model will attempt to help improve HR practitioner's person-environment interaction with AI recruiting. Within the Evaluative Framework, Latack and Havlovic (1992) describe problem-focused coping by distinguishing between cognitive and behavioral dimensions.

Cognitive coping strategies may include self-talk and mental planning, for instance, by emphasizing the positive aspects of the situation or making sure to maintain an organized and well-planned process (Latack & Havlovic, 1992). Whereas, behavioral strategies involve active participation, such as actively seeking out more information about the situation (Latack & Havlovic, 1992). When implementing a cognitive control approach, an individual may view the situation in an optimistic manner, while a behavioral control approach will adopt a proactive stance and initiate change (Latack & Havlovic, 1992). Moreover, a cognitive escape approach may involve the individual attempting to avoid thinking about the situation. In contrast, a behavioral escape approach involves diverting attention to other work responsibilities (Latack & Havlovic, 1992). Thus, further classification of cognitive and behavioral coping dimensions can be made into control and escape subdimensions, as summarized in Table 1.

Table 1: *Evaluative Framework Applied to Coping Measures*

Method	Dimensions of Problem-Focused Coping
Cognitive	**Control** Planning, organizing, prioritizing assignments **Escape** Try to pay attention to only your duties in order to overlook difficulties
Behavioral	**Control** Delay or leave undone some of normal job responsibilities **Escape** Get busy with other things in order to keep my mind off the problem

Note. The emotion-focused coping dimensions are not included.

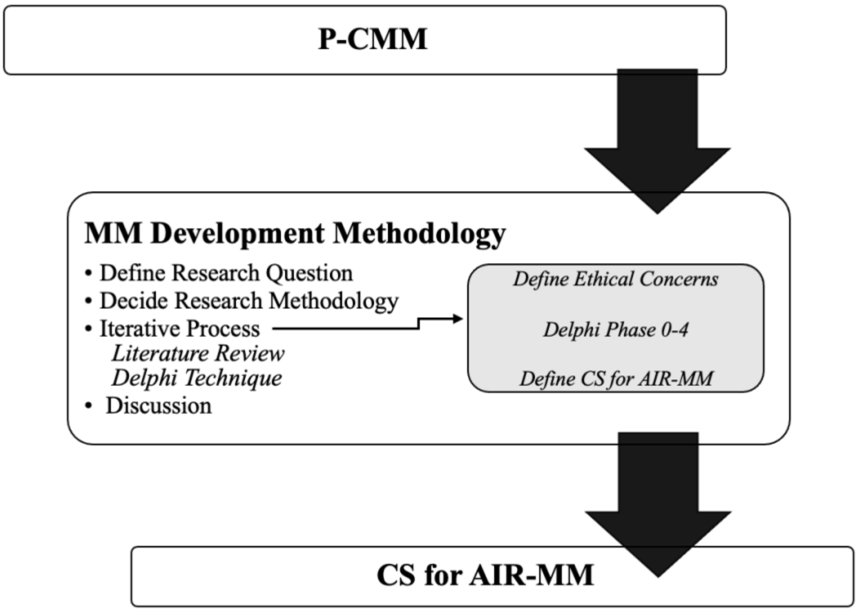
By utilizing this evaluative framework, we aim to categorize the most pressing ethical challenges associated with using AI recruiting and identify the corresponding coping strategies to mitigate them. By doing so, we will be able to develop an overall maturity model consisting of HR practitioners' most effective coping strategies.

3.0 Research methodology

3.1 Research Design

In this study, we aim to provide insights regarding how HR practitioners can cope with the ethical challenges posed by AI recruiting during the selection process, and to develop a maturity model to ensure continuous improvement in the area. Maturity models (MM) have been proven to be an important instrument for improving organizational positioning and providing improved solutions for transformation (Cho et al., 2023; Curtis et al., 2001). An organization's maturity refers to its capacity for continuous improvement within a particular discipline (Becker et al., 2009). In the present study, we combine ethical concerns regarding AI recruiting and corresponding coping strategies to propose Coping Strategies for AI Recruiting Maturity Model (CS for AIR- MM), a maturity model for ensuring effective and reliable AI coping strategies (Cho et al., 2023). Figure 1 displays a detailed overview of the research methodology applied to adhere to this objective.

Figure 1: *A Flowchart of CS for AIR-MM, adapted from Becker et al. (2009) and Cho et al. (2023)*



Note. P-CMM = people capability maturity model, MM = maturity model.

3.1.1 Delphi Method Methodology

The Delphi method is used to gather opinions and viewpoints from experts on a particular matter (Miller & Murry, 2015). The technique has undergone rigorous review and assessment, and it is commonly applied in situations where conventional methods may not be applicable or effective, such as when dealing with intricate subject matters. As is the case with our thesis, which involves a complex topic (Hsu & Sandford, 2007; Merfeld et al., 2019).

This method provides a systematic and structured approach to gathering and analyzing expert opinions (Hartl & Hess, 2017). Typically, experts are asked to provide their opinions on a particular topic during multiple rounds of research. Their responses are then analyzed and compiled (Okoli & Pawlowski, 2004). This process is repeated over several phases, with each phase allowing for the refinement and further development of the experts' responses (Powell, 2003). This method offers several advantages for our research as it enables a smaller sample size, permitting new or emerging topics to be evaluated and allowing the panel to be geographically diverse (Miller & Murry, 2015; Williamson, 2002). As the method synthesizes expert options it will be possible to ensure that our findings are comprehensive and representative of the broader field of study (Hartl & Hess, 2017; Okoli and

Pawlowski, 2004). Further, the technique is appropriate since it is typically used in situations where there is a lack of adequate historical data and human judgment is required, such as in the case of ethical AI recruiting (Wright et al., 1996). Additionally, the method is recognized as having particular application in the assessment of strategic initiatives in the technology sector (Merfeld et al., 2019).

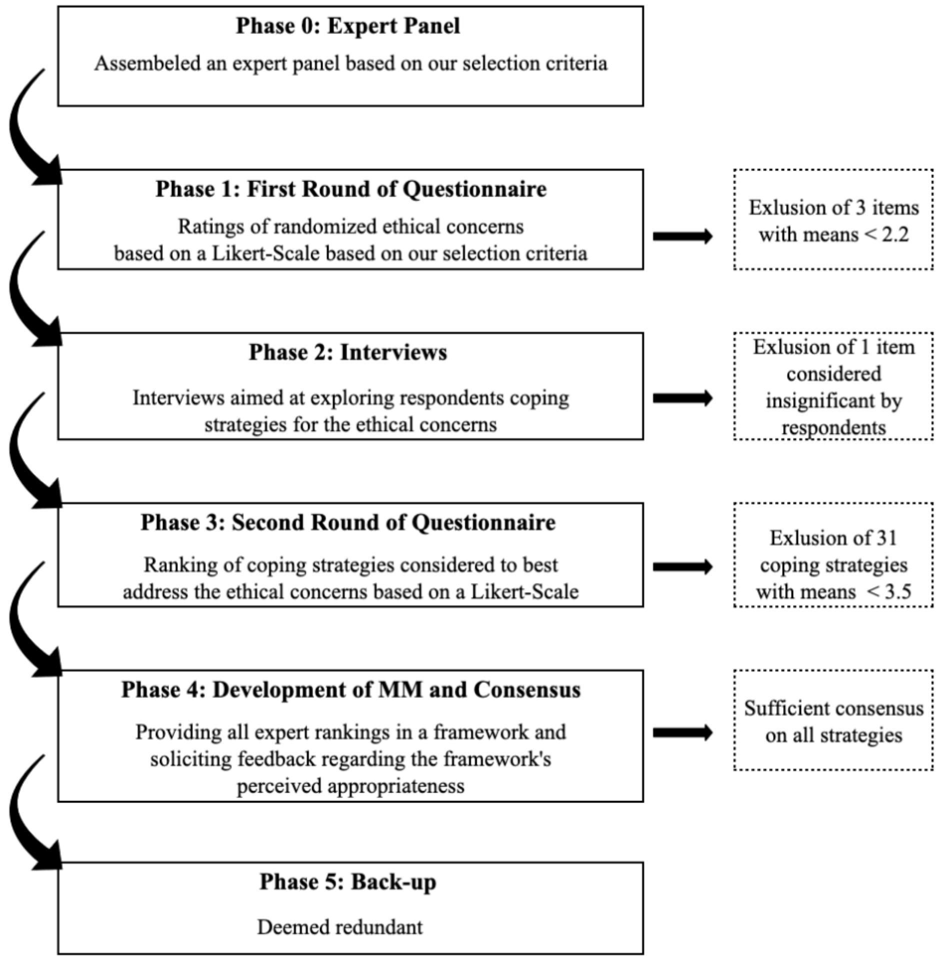
The Delphi method, however, has some shortcomings and disadvantages. Due to multiple rounds of data collection and analysis, this method can be time consuming and resource intensive (Okoli & Pawlowski, 2004; Powell 2003). There is also a possibility of losing respondents if they find the process to be too time-consuming. Further, the method may be prone to bias if the experts are not properly selected or if the questions are poorly constructed (Hartl & Hess, 2017; Powell 2003).

Despite these shortcomings, and due to its proven effectiveness with smaller sample sizes and expert consensus, the Delphi technique is the most appropriate method to address the main objective of this thesis, which is how AI practitioners can cope with ethical concerns related to AI recruiting (Hartl & Hess, 2017; Okoli & Pawlowski, 2004). Additionally, as our research question is relatively underexplored but has rising interest, the use of the Delphi method is of sound reasoning. Notably, our thesis made use of both qualitative and quantitative methods, allowing us to leverage the strengths of each approach (Bell et al., 2019).

3.2 Research Procedure

Drawing on the suggestions made by Williamson (2002) and Barnes and Mattsson (2016), our Delphi study incorporated five distinct phases; Expert Panel, First Round of Questionnaire, Interviews, Second Round of Questionnaire, and Development of MM and Consensus, as summarized in Figure 2. We determined that our initial plan, which included a sixth phase, Back-up, was unnecessary for achieving our objectives. Due to the high consensus, we found that conducting five phases yielded sufficient understanding and insights, without any significant additional value that the sixth phase would have provided (MacCarthy et al., 2003).

Figure 2: *The Delphi Process, adapted from Barnes and Mattsson (2016) and Merfeld et al. (2019)*



Note. MM = maturity model.

3.2.1 Research Validity and Reliability

Saunders et al. (2019) assert that the credibility of a research is determined by the reliability and validity of the research design. Golafshani (2003) defines reliability as the "idea of replicability or repeatability of results or observations" (p. 598), whereas validity refers to whether the intended outcome was achieved or whether the results are accurate. Several factors can pose threats to the reliability of our study; participant error, subject or participant bias, and observer error or bias (Edmonds & Kennedy 2017; Saunders et al., 2019). To avoid these threats, several measures have been considered. Our methodology is designed to minimize limitations such as bias by carefully selecting respondents based on our identified criteria, specified in section 4.1. Furthermore, both the questionnaire and interview questions have been thoroughly evaluated during the development process. This has enabled us to create a robust research design, which maximizes the benefits of the

Delphi method.

3.2.2 Research Ethics

Dawson (2007) argues that both participants and the information they provide during a research process should be treated fairly and honestly. The researcher must therefore act in accordance with the rights of the subjects and individuals affected by the project (Bell et al., 2019; Cooper & Schindler, 2008; Saunders et al., 2019). Several measures are taken to ensure that these rights are protected.

Our research did not require NSD approval due to the nature of the information we have gathered. However, we ensured the privacy of all participants by protecting personal information in a highly confidential and anonymous manner (Saunders et al., 2019). The responses were protected where information was limited to us and the respective participants. Further, we kept their personal information, such as e-mail addresses and names, in password-protected files that were accessible only to us. Additionally, participation in the study was voluntary and participants were properly informed of the purpose of the research and the methods for storing and deleting their data before they became involved in the study (Bell et al., 2019). Moreover, we obtained participant consent, in line with the ethical guidelines outlined by Dawson (2007). For this purpose, we distributed a participant agreement form, clearly outlining the purpose and usage of the collected responses. This ensured that all concerned parties were in complete agreement before proceeding with the study (Bell et al., 2019).

3.2.3 Main Concepts

The concepts addressed in our study undergo changes throughout each phase. In phase one, our main concepts included the four areas of ethical concerns identified in section 2.1, namely privacy, performance of AI, transparency and accountability, and job concerns. These concepts were first carefully evaluated by the expert panel to gain insights into their impact on AI recruiting processes during the selection process. Moving to phase two, the concepts shifted to include 10 sub-themes or concerns that emerged as a result of the analysis conducted in phase one. These sub-concerns served as focal points for further exploration and understanding in interviews with the expert panel. In phase three, the concepts consisted of coping strategies that emerged from the analysis of findings in phase two. These concepts provided valuable insights into how HR professionals can effectively cope with the ethical challenges posed by AI recruiting. Lastly, in phase four, which aimed to achieve consensus among the panel, the concepts were comprehensive, covering the ethical concerns, sub-concerns, and coping strategies. This phase aimed to consolidate the panel's opinions and clarify the understanding of how HR professionals can navigate ethical challenges in the context of AI-driven recruitment processes with different coping strategies.

3.3 Analytical Approach

We have adopted an analytical approach for the Delphi technique, where each phase's analysis has been completed before proceeding to the next (Hsu & Sandford, 2007). This is due to the interdependence of data between subsequent phases and the preceding ones, in which each phase relies on the findings of the previous phase (Miller & Murry, 2015). As such, we have found it appropriate to compile our methodology, analysis, and findings sections accordingly. The combined presentation of the method, analysis and findings ensures a more comprehensive and meaningful account of our research methodology (Hsu & Sandford, 2007). Moreover, this approach offers a holistic view of the research process, ensuring that the data is presented in a coherent and structured manner (Williamson, 2002).

4.0 Method, Analysis & Findings: Phase 0-4

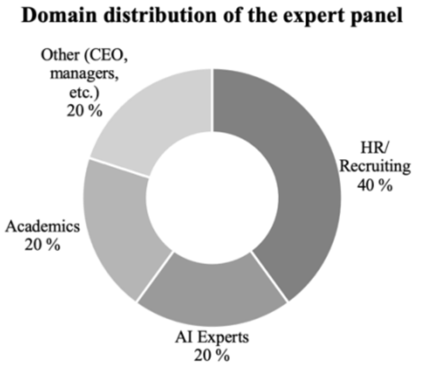
4.1 Phase 0: Expert Panel

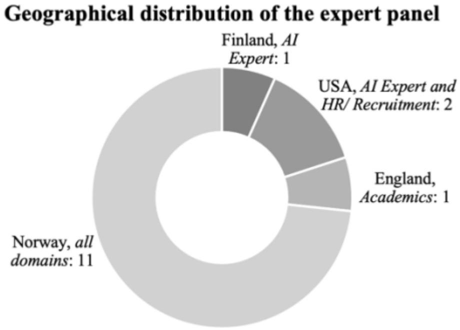
The first step in conducting a Delphi study, gathering an expert selection, is essential for the quality of the outcomes. Improper selection of participants can result in selection bias, which negatively impacts the method's validity (Tersine & Riggs, 1976). According to Tersine and Riggs (1976), experts should thus be selected based on four fundamental criteria. First, experts should possess fundamental knowledge of the problem domain. Second, Tersine and Riggs (1976) assert that the candidates must have the ability to apply that knowledge effectively. Third, they should have substantial experience in their respective fields, and have the necessary time and willingness to participate fully in the study until its completion. Finally, the fourth and last requirement states that experts should be committed to dedicating a thorough and conscientious effort to their participation in the study (Tersine & Riggs, 1976).

Based on these fundamental criteria, our study established five selection guidelines for identifying suitable experts. Respondents were required to have either: (1) ≥ 5 years of experience in recruitment, (2) academic knowledge of and/or expertise on ethical considerations surrounding AI, or to be either (3) currently using AI as part of their recruiting process or have within the past three years, or (4) be employed by a company that offers AI recruitment tools (e.g., CEO, manager, HR). Furthermore, all respondents should (5) offer full participation and dedication to the study.

We identified candidates through professional social media networks, mainly LinkedIn, and contacted organizations and individuals that met our criteria. Through personal messages and emails, we explained the purpose of the study and the extent to which their assistance was required. This enabled us to disclose the approximate amount of time that would be involved, allowing us to identify experts who were willing to take part fully and avoid dropouts. Among the 62 experts contacted, 20 respondents from four different countries agreed to participate in our expert panel. However, in the subsequent phases, it was reduced from 20 to 19 to 15 respondents. Accordingly, we observed an overall dropout rate of 25%, lower than the standard dropout rate of approximately 30% found in previous research by Saunders et al. (2019). The final panel consisted of a total of six individuals from the HR or recruitment domain all with AI recruiting experience, three academics, three AI experts, and three others, denoting leaders, CEOs, and other managerial positions from companies offering AI recruitment tools, as summarized in Figure 3 and 4. We convened an expert panel comprising individuals who satisfied at least one of our criteria, along with fulfilling criterion (5). Specifically, we had nine participants who met the qualifications of criteria (1) and (3), three participants who fulfilled criteria (2), and an additional three participants who satisfied criteria (3) and (4). As such, we were able to gather a group of participants that exhibited heterogeneity, as such groups have been found to generate solutions of high quality and acceptance, while actively preventing cognitive biases (Winkler & Moser, 2016).

Figure 3 and 4: *Overview of the Final Expert Panel, N=15*





4.2 Phase one: First Round of Questionnaire

4.2.1 Method

Bell et al. (2019) argues that it can be difficult to curate well-structured questions. Thus, we thoroughly designed our questionnaire following the observations made in our literature review. In order to begin gathering data, we developed a set of questions and prompts to guide our study (Bell et al., 2019). The literature review provided us with the basis for developing these questions and propositions, which focused on key ethical concerns associated with the use of AI recruiting. Four areas of ethical concerns were identified, including privacy, performance of AI, transparency and accountability, and job concerns, as summarized in section 2.1. These areas further shaped our Delphi study.

To minimize participation barriers, experts were provided with both Norwegian and English questionnaires (Barnes & Mattsson, 2016). Each step of the translation process underwent a rigorous translation-translation-back process to limit the risk of bias and ensure the accuracy of the translation (Chen & Boore, 2010). To further limit any additional bias, the wording and formulation of items were reviewed by an experienced researcher (our supervisor) (Winkler & Moser, 2016). For the purpose of enhancing the reliability of the data and increasing response rates, all questionnaires were administered online using Qualtrics (Saunders et al., 2019). This enabled us to ensure anonymity and international accessibility (Bell et al., 2019). As our research design revolves around expert opinions, respondents with inadequate knowledge or experience are likely to provide uninformed responses, which reduces the reliability of the data (Saunders et al., 2019). By setting clear and specific requirements for our experts and conducting a careful selection process, we were able to mitigate the risk of receiving compromised or biased responses (Bell et al., 2019). We further mitigated the potential for inaccurate responses, by opting for questionnaires being completed anonymously and without our intervention, as this approach reduces the likelihood of socially desirable responses from the participants (Bell et al., 2019; Saunders et al., 2019). As part of phase one in our Delphi study, we employed a structured and quantitative approach, aimed at classifying the identified ethical considerations (Bell et al., 2019). Based on four main areas of ethical concern, respondents were asked to rank 15 items on a five-point Likert-Scale ranging from 1 (low concern) to 5 (high concern), as summarized in Table 2.

Table 2: *Ethical Concerns*

Item	Ethical Concerns
1	Data collection through third parties
2	Ownership over candidate data
3	Storing candidate data
4	Obtaining job applicant's consent
5	Accuracy predicting future job performance
6	Hiring discrimination
7	Valid and reliable practices
8	Understandability of AI
9	Transparency amid employer and candidate
10	Emotional and psychological complexities
11	Trust in AI
12	Data collection through social media
13	Threat to employment of human recruiter
14	Oversurveillance of human recruiters
15	AI is not really a helpful tool

4.2.2 Analysis

In accordance with Hsu and Sandford (2007), measures of central tendency such as means, mode and median, as well as level of dispersion, such as standard deviation, were included in the analysis. Given the limited size of the dataset, which included only 19 respondents, Excel was employed as the tool for data analysis.

In line with the approach taken by Doke and Swanson (1995), we utilized the mean variable as a measure to rank the items in our Delphi study. Chan (2022) emphasizes the importance of displaying the findings mean and standard deviation in order to further assess which items are significant for further research. In a five-point Likert scale, consensus can be measured by the mean value being ≥ 3.00, according to Chan (2022). Warner and Washburn (2009), however, recommend using a higher mean value. Our study consists of the same sample size and five-point Likert scale as Warner and Washburn (2009). Based on these factors, the mean score should accordingly be 3.5 or greater to qualify as consensus in our study. Given the preliminary nature of the Delphi study's first phase, it was decided to avoid disregarding items with mean values below 3.5 immediately without further investigation.

4.2.3 Findings

During the analysis of phase one, we observed certain patterns, as summarized in Table 3. Specifically, items 3, 4, and 10 displayed significantly low means of 2.2 and 2.3, although accompanied by high standard deviations. On the other hand, items 13, 14, and 15 exhibited relatively lower mean values and smaller standard deviations, indicating a consensus among respondents regarding the level of concern. In order to effectively differentiate between items with low and high standard deviations, a threshold for the mean value of ≥ 2.2 was established, considering the minimal spread of standard deviation in items below this value. This threshold of ≥ 2.2 reflected sufficient consensus achieved in phase one. Regarding the mode, the majority of items exhibited a predominant distribution around the values of 4 or 5, as well as 1 or 2, reflecting respondents' substantial agreement or disagreement with the respective ethical concerns (Altman & Bland, 2005). Additionally, the median values were closely aligned with the mean values, suggesting relatively limited dispersion or variability within the data (Altman & Bland, 2005).

Table 3: *Descriptive Statistics of Phase one*

Item	N	Mean	Median	Mode	SD
1	19	2.56	2.00	1[a]	1.236
2	19	2.89	3.00	4	1.453
3	19	2.33	2.00	1	1.225
4	19	2.22	2.00	1[a]	1.202
5	19	3.67	4.00	4	1.225
6	19	3.44	4.00	4	1.509
7	19	3.67	4.00	5	1.581
8	19	3.33	4.00	4	1.000
9	19	3.44	4.00	4	1.424
10	19	2.33	2.00	1	1.581
11	19	3.44	4.00	4	1.424
12	19	4.00	5.00	5	1.414
13	19	1.11	1.00	1	.333
14	19	1.56	2.00	2	.527
15	19	1.67	1.00	1	.866

Note. [a] Multiple modes exist; the smallest value is shown. N = sample size. SD = standard deviation.

Elaborating on the results in Table 3, we identified a final ranking of all the ethical concerns in Table 4. Our respondents highlighted three key ethical concerns as significant: data collection through social media, accuracy in predicting future job performance, and valid and reliable practices. These concerns emerged as the most prominent areas of focus, emphasizing their importance in the context of ethical considerations. By implementing the mean threshold of 2.2, it was decided that item 13, 14 and 15, all related to job concerns, would be excluded from further phases. As such, we were able to identify the most pressing ethical issues and categorize them from most to least concerning. Thus, enabling us to identify the primary challenges we needed to address in phase two of the Delphi study.

Table 4: *Ranking of Ethical Concerns*

Ranking	Item	Ethical Concerns
1	12	Data collection through social media
2	5	Accuracy predicting future job performance
3	7	Valid and reliable practices
4	6	Hiring discrimination
5	9	Transparency amid employer and candidate
6	11	Trust in AI
7	8	Understandability of AI
8	2	Ownership over candidate data
9	1	Data collection through third parties
10	3	Storing candidate data
11	10	Emotional and psychological complexities
12	4	Obtaining job applicant's consent
13	**15**	**AI is not really a helpful tool**
14	**14**	**Over Surveillance of human recruiters**
15	**13**	**Threat to employment of human recruiter**

Note. Bolded items did not meet the threshold.

4.3 Phase Two: Interviews

4.3.1 Method

Phase two involved conducting interviews in order to gain a deeper understanding into how our respondents cope with the ethical concerns associated with AI recruiting, and which coping strategies they utilize. We conducted semi-structured, one-to-one interviews (Bell et al., 2019). Our study gains much benefit from semi-structured interviews as it is used to validate and explore the findings of the previous questionnaire (Saunders et al., 2019). To be eligible to participate in our study, respondents were required to complete all questionnaire phases;

however, the interview was optional.

We created our interview guide by utilizing the results of our initial questionnaire to investigate potential coping strategies for the identified ethical concerns (Kallio et al., 2016). A total of 12 questions were asked in the interview, corresponding with the 12 ethical concerns ranked in phase one. To obtain sufficient data, the language of the questions needed to be adjusted according to the background of the participants (Bell et al., 2019). In order to ensure that the subject matter was maintained, we repeated the translation-translation-back process (Chen & Boore, 2010). The interviews were conducted over Zoom and in-person and lasted approximately 45 minutes to 1 hour.

At the beginning of each interview, we stated the findings from the previous phase, offering each respondent the option to reevaluate their own answer based on the opinions of the panel (Williamson, 2002). This was continuously carried out at the beginning of each phase to ensure the content validity (Bell et al., 2019; Saunders et al., 2019).

Each interview was recorded with the experts' consent and transcribed verbatim (Bell et al., 2019). As a means of preventing information loss, transcriptions were completed promptly following the interviews. After the transcripts were complete, we reviewed the recordings of each interview once again to mitigate the risk of misinterpreting words, mishearing, or misunderstandings (Easton et al., 2000). Following the completion of the transcriptions, the recordings were deleted. To ensure anonymity, the interviewees were assigned an ID consisting of a randomized number and a letter code denoting gender (F for female, M for male) and profession (A for academic, P for professional) in the transcription. In order to further ensure confidentiality, the transcripts were stored in separate files that were password-protected (Bell et al., 2019; Saunders et al., 2019).

4.3.2 Analysis

We engaged in a two-step process to categorize the data obtained from the interviews. Following Strauss and Corbin's (2008) recommendation, we developed our initial set of categories by reviewing the terminology used by the interviewees and ensuring consistency with existing literature (Campbell et al., 2013; Saunders et al., 2019). In correspondence with phase one, a total of 10 sub-themes were proposed based on the previously identified ethical concerns. These categories included Data Ownership, Data Collection, Data Storage, Consent, Valid and

Reliable Practices, Predicting Job Performance, Hiring Discrimination, Social Media, Understandability and Trust. These categories formed the foundation for the following unitization process, in which we attached relevant coping strategies to each category (Saldaña, 2020).

During the development of our categories and codes, we sought to ensure their consistency, accuracy, and reproducibility, on recommendation by Campbell et al. (2013). For this purpose, we conducted independent analyses of the transcribed interviews before meeting to review and refine them. Using this approach, we were able to evaluate the consistency and precision of our codes among us, as well as verify intercoder reliability by assuring uniform coding of the same data (Campbell et al., 2013).

4.3.3 Findings

A total of seven participants agreed to participate in the interview process, and we interviewed a minimum of one representative from each of our selection criteria. Upon revisiting the results from phase one, two respondents requested revisions of their initial responses. One respondent reevaluated their initial job concerns statement. The respondent lowered their rating from 5 (high concern) to 4 (concern), resulting in a closer consensus among the experts. Additionally, another respondent reevaluated their initial statement on data ownership. The respondent increased their rating from 3 (neutral) to 4 (concern).

We constructed an analytical framework of strategies that served as the basis for our further analysis, which we conducted using Latack and Havlovic's (1992) Evaluative Framework. We analyzed each coping strategy based on whether it reflected a behavioral-focused coping strategy or a cognitive-focused coping strategy. Moreover, we classified each coping strategy based on the authors' control and escape dimensions, resulting in a total of 66 different coping strategies (Latack & Havlovic, 1992), as summarized in Table 5. In Table 5, it is observed that the behavioral control dimension encompassed the highest number of strategies, indicating its prominence within the framework. The popularity of this coping strategy indicates that our respondents prefer proactive solutions to the ethical concerns. This may be explained by the fact that such strategies involve direct action and may enable them to develop a sense of control over the situation (Latack & Havlovic, 1992). Furthermore, the cognitive escape dimension emerged as the second most prevalent strategy. This is presumably due to the fact that cognitive escape strategies incorporate measures that allow professionals to process and gain a better understanding of their situation (Latack & Havlovic, 1992). This is reasonable for an unfamiliar and emerging topic such as AI recruiting.

Table 5: *Overview of Coping*

Ethical Area of Concern	Coping Strategy Terminology	Number of Coping Strategies
Privacy: *data ownership, data collection, data storage, consent*	Behavioral Control	16
	Behavioral Escape	1
	Cognitive Control	1
	Cognitive Escape	5
Performance of AI: *valid and reliable practices, predicting job performance, hiring discrimination*	Behavioral Control	15
	Behavioral Escape	2
	Cognitive Control	0
	Cognitive Escape	5
Transparency and Morals: *social media, understandability, trust,*	Behavioral Control	14
	Behavioral Escape	3
	Cognitive Control	1
	Cognitive Escape	4

4.4 Phase Three: Second Round of Questionnaire

4.4.1 Method

During phase three of the study, participants were presented with the 66 coping strategies derived from phase two (see Appendix 6). The participants were further invited to provide feedback on these coping strategies. This step was undertaken with the aim of incorporating coping strategies used by participants who did not take part in the initial interviews, as well as offer an opportunity for the interview participants to reassess their own responses based on the opinions of the larger panel. In this way, we ensured that the data collection was comprehensive and inclusive (Powell, 2003). However, there were no respondents who requested to propose additional coping strategies or modify the existing strategies when revising the previous results. Thus, we proceed with the 66 identified coping strategies presented in Appendix 6.

The purpose of this questionnaire was to measure participants' perception of the efficacy of the 66 coping strategies in managing ethical concerns. To ensure reliability, limit bias and inaccurate responses, we followed the same steps as in phase one when developing the questionnaire (Barnes & Mattson, 2016). To measure the extent to which each coping strategy effectively tackled the corresponding ethical concern, we utilized a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Participants were asked to indicate their level of agreement on this scale, providing a quantitative assessment of the coping strategy's perceived efficacy in managing the ethical concern at hand. The questionnaire was comprehensive with regard to its content, measuring the effectiveness of all 66 identified coping strategies, comprising a total of 18 questions.

4.4.2 Analysis

Out of the original sample size of 19 participants, a total of 17 individuals responded to the questionnaire. However, two respondents did not complete the questionnaire entirely, and their incomplete responses were excluded from the subsequent analysis. Consequently, the final analysis was conducted with a reduced sample size of 15 participants. The lower response rate could be attributed to the comprehensive nature of the questionnaire, which likely demanded a significant investment of time and effort from the participants.

Consistent with the methodology employed during phase one, we applied the measurement recommendations put forth by Hsu and Sandford (2007), encompassing statistical measures such as mean, mode, median, and standard deviation. Given the smaller sample size, Excel was utilized as the analytical tool. Additionally, we followed the suggestion proposed by Warner and Washburn (2009) to exclude items with a mean score less than 3.5, ensuring a focused analysis on coping strategies that received comparatively higher agreement ratings from the participants.

4.4.3 Findings

Table 6 reveals that a considerable number of items exhibit a mean value of 3.5 or below. By utilizing the mean value threshold at ≤ 3.5, we ensured the inclusion of items 18, 22, and 31, which were identified as highly concerning in phase one, however, displayed mean values as low as 3.5 in phase two. The deliberate threshold decision aimed to incorporate coping strategies addressing the ethical areas of accuracy in predicting job performance, valid and reliable practices, and hiring discrimination, which ranked as the second, third, and fourth most significant concerns in phase one. Additionally, a high standard deviation can be observed for some of these items, indicating a lack of agreement among experts, further supporting a threshold for the mean value of ≤ 3.5.

Items 8, 12 and 14 all have the highest mean value of 4.88. The median indicates a balanced distribution, as it closely aligns with the mean value. The standard deviation of these items is .354, indicating a low level of variability or dispersion. Thus, indicating a significant level of consensus among the panel regarding the high level of concern related to these items. The majority of items in the dataset exhibit medians that are comparable to, or slightly deviate from the mean values. This suggests a limited degree of dispersion in the data. Additionally, a mode value of 5 is observed for most of the items, indicating that a substantial number of respondents rated these strategies as of high concern. This finding aligns with our expectations, considering that the coping strategies were specifically designed to address ethical areas of high to medium concern.

Table 6: *Descriptive Statistics of Phase three*

Item	N	Mean	Median	Mode	SD
3	15	4.00	4.00	4[a]	1.069
6	15	4.38	5.00	5	1.061
7	15	4.38	5.00	5	1.061
8	15	4.88	5.00	5	.354
12	15	4.88	5.00	5	.354
13	15	4.63	5.00	5	.518
14	15	4.88	5.00	5	.354
15	15	4.13	5.00	5	1.246
16	15	4.75	5.00	5	.463
18	**15**	**3.75**	**3.50**	**3**	**.886**
19	15	3.88	4.50	5	1.458
20	15	3.88	4.00	5	1.126
22	**15**	**3.50**	**3.50**	**3[a]**	**.926**
24	15	4.00	4.00	4	.756
25	15	4.00	4.50	5	1.195
26	15	4.75	5.00	5	.463
28	15	4.75	5.00	5	.707
29	15	4.25	5.00	5	1.488
30	15	4.25	4.50	5	.886
31	**15**	**3.88**	**4.00**	**3[a]**	**.835**
32	15	4.25	4.00	4	.707
33	15	4.38	4.00	4	.518
35	15	4.63	5.00	5	.518
36	15	4.50	4.50	4[a]	.535
40	*15*	*3.75*	*4.00*	*4*	*1.035*
42	15	*3.50*	*3.00*	*3*	*.756*
43	15	4.00	4.50	5	1.195
44	15	4.88	5.00	5	.354

45	15	4.25	5.00	5	1.035
47	15	4.38	5.00	5	.916
48	*15*	*3.63*	*3.50*	*3*[a]	*1.408*
49	15	4.38	5.00	5	.916
50	15	4.63	5.00	5	.744
51	15	4.25	4.50	5	.886
52	15	4.50	5.00	5	.756
56	15	4.13	5.00	5	1.458
57	*15*	*3.50*	*3.00*	*3*[a]	*1.309*
58	15	4.13	5.00	5	1.246
60	15	4.00	4.50	5	1.195
65	*15*	*3.75*	*4.00*	*5*	*1.389*

Note. Items below threshold are not included. Bolded items = high concern in phase one, cursive items = medium concern. [a] Multiple modes exist; the smallest value is shown. N = sample size. SD = standard deviation.

After applying the threshold criteria, a total of 40 coping strategies were identified in the final list of items, with 26 strategies being excluded. This rigorous process allowed us to pinpoint the coping strategies that were perceived as most effective in addressing ethical concerns, emphasizing the most significant coping strategies. Through the development of this comprehensive overview, we established a sound groundwork for developing our maturity model, which will be applied subsequently in the fourth phase.

4.5 Phase Four: The Development of MM & Consensus

4.5.1 The Development of the Coping Strategies for AI Recruitment Maturity Model

4.5.1.1 People Capability Maturity Model

Following the identification of the 40 most effective strategies for coping with the ethical issues at hand presented in Table 6, a comprehensive analysis was conducted to construct our maturity model. The analysis commenced by categorizing each strategy according to its maturity level, based on the People Capability Maturity Model (P-CMM) proposed by Curtis et al. (2001). As described by the authors, organizational work processes evolve through various maturity levels. The Initial Level 1 is characterized by a lack of consistent work methods, with ad hoc processes that are reinvented for each project and often appear chaotic (Curtis et al., 2001). Moving to the Managed Level 2, organizations establish a stable environment by deploying common processes across the organization, laying the groundwork for implementing advanced practices (Curtis et al., 2001). At the Defined Level 3, best practices are identified and integrated into a common process, allowing individuals to apply proven approaches to the specific context of their work. The Predictable Level 4 involves managing processes using performance data, allowing for statistical characterization and prediction of critical process performance (Curtis et al., 2001). Finally, at the highest level of maturity, the Optimizing Level 5, organizations leverage quantitative knowledge to continuously improve processes, using data insights to identify areas for enhancement (Curtis et al., 2001).

4.5.1.2 Coping Strategies for AI Recruiting Maturity Model

By utilizing P-CMM and its five maturity levels, we assessed the organizational maturity of the 40 identified coping strategies to define our CS for AIR-MM. At the Initial Level 1, no strategies were identified, as this level does not encompass any specific process areas according to Curtis et al. (2001). Coping strategies that focused on the establishment of structured guidelines and policies to ensure ethical use of AI in recruitment were classified at the Managed Level 2. These strategies were associated with training and development of employees and the AI tools, communication with candidates, coordination within the organization, as well as performance management of the AI technology (Curtis et al., 2001). At this level, our focus was on incorporating fundamental coping strategies that should be established before any organization utilizes AI recruiting. At the Defined Level 3, coping strategies emphasizing development of knowledge and skills of employees, and enhancement of process capabilities within the firm were outlined. These strategies were primarily focused on competence analysis of the AI tools and competence development of HR professionals (Curtis et al., 2001). In this level, we included strategies that emphasized that AI recruiting is utilized by qualified individuals who possess the necessary knowledge to assess the ethical implications of the AI tools. In the Predictable Level 4, strategies were focused on managing capabilities of the AI and employees, as well as competency-based processes within the firm to establish a predictable and stable environment in AI recruiting. This level integrates coping strategies related to organizational capability management and competency integration (Curtis et al., 2001). In Level 4, we incorporated strategies focused on effectively managing the knowledge and capabilities acquired in Level

3. Lastly, strategies aligned with the Optimizing Level 5 that emphasize continuous capability improvement within the organization were identified (Curtis et al., 2001). At this level, we focused on including strategies that encompassed the integration of the managed knowledge and capabilities attained in Level 4 into the organization's routine operations, serving as a mechanism to promote the continuous ethical use of AI recruiting.

Following the categorization of each strategy into its respective level, we began further reviewing and refining them. Notably, within the same level, certain strategies displayed comparable linguistic expression and semantic content, thus we opted to streamline and group them together. Furthermore, we adjusted the wording to enhance comprehensibility (Harji et al., 2016; Sandelowski et al., 2007). The objective was to create a more user-friendly and accessible model, ensuring ease of reading and utilization.

These efforts resulted in a total of 33 strategies, summarized in Table 7. Sixteen strategies at Level 2 were identified, of which six dedicated to addressing privacy concerns, six aimed at addressing AI performance concerns and four focused on transparency and accountability. Further, seven strategies for Level 3 were identified, encompassing one strategy related to privacy concerns, four addressing AI performance concerns, and two concerning transparency and accountability concerns. Moreover, five strategies for Level 4 were identified, with four aimed at addressing AI performance concerns and one targeting transparency and accountability concerns. Lastly, five strategies for Level 5 were identified, with three focusing on AI performance concerns and two targeting accountability and transparency concerns.

Table 7: *Overview of Coping Strategies placed in Maturity Levels*

Maturity Level	Privacy Concerns	AI Performance Concerns	Transparency and Accountability Concerns
Level 2: Managed	Ensure consent is obtained and compliance with GDPR legislations is maintained responsibly (Behavioral Control) Utilize a terms of use agreement that specifies data collection and data storage (Behavioral Control) Consider that the data is the property of the candidate, which you are merely borrowing (Cognitive Control) Provide candidates with information in accordance with GDPR (Behavioral Control) Control over the data the AI tools have access to (Behavioral Control) Ensure safe storage by not selling nor sharing the data parties (Behavioral Control)	Ensure that the AI tools are equipped with all the necessary data (Behavioral control) Employ anonymized CVs, where the AI tools remove all non-relevant information, allowing assessments to focus solely on the candidates' qualifications (Behavioral Control) Identify job-relevant parameters and program AI to exclusively consider these factors to avoid discriminatory behavior (Behavioral Control) Limit final stages of the recruitment process to human recruiters exclusively (Behavioral Control) Use tools to carry out simple requirements and handling the more complex aspects of the tasks oneself (Behavioral Control) Maintain usual operating procedures when using AI (Behavioral Escape)	Obtain consent before collecting data from Some and avoid excessive inquiries (Behavioral Control) Use a third party to gain knowledge and understandability (Behavioral Control) Ensure that the candidates' information will not be misused (Behavioral Control) Rely on several steps in the recruitment process in order to detect deviations within the AI tools training (Behavioral Control)

Level 3: Defined	Implement an automated data deletion policy for unqualified candidates (Behavioral Control)	Assure that employers understand psychometrics, to verify the AI developers claims (Behavioral Control) Require AI vendors to provide evidence of the validity of their AI tools (Behavioral Control) Ensure quality of the AI tools by continuously comparing their results to those of human recruiters (Behavioral Control) Strengthen the training of AI tools by providing them with diverse information, akin to the training of HR personnel (Behavioral Control)	Gain an understanding of psychometrics to assess the validity and liability of measurements to increase trust in the AI tools (Behavioral Control) Use an unbiased third party to validate the AI- tool (Behavioral control)
Level 4: Predictable		Assess the predictive validity of the AI-tool (Behavioral Control) Improve the AI tools through user/client input (Behavioral Control) Regularly test the AI-tools to detect any inconsistencies or deviations, to reduce discriminatory behavior in AI (Behavioral Control) Identify the qualifications required to succeed in a position and incorporates	Consider the predictive accuracy of the collected data in determining a candidate's job success (Cognitive Control)

	these into the AI algorithm (Cognitive Control)	
Level 5: Optimizing	Ensure that data input is accurate by human verification (Behavioral Control) Obtain evidence of the AI-tool's validity from the developer (Behavioral Control) View AI as a tool for assistance rather than a self-sufficient tool (Behavioral Escape)	Maintain transparency in the AI recruitment process by consistently seeking candidates' consent for AI tools, before implementing the tools (Behavioral Control) Regularly test and research the tool before use (Behavioral Control)

Note. Similar coping strategies have been grouped.

4.5.2 Method

In phase four, we sought feedback on the initial version of our framework. In this questionnaire, the expert panel was presented with the findings of phase 3, including all 33 coping strategies. In developing this questionnaire, we followed the same rigorous steps used in phases 1 and 3 to ensure reliability, minimize bias, and mitigate inaccurate responses. The questionnaire consisted of a single question, seeking the respondents' agreement or disagreement with the model, along with an opportunity to provide feedback. The questionnaire utilized a nominal scale with the values of "yes" and "no" to capture the respondents' responses (Pasukeviciute & Roe, 2001).

4.5.3 Analysis

A total of 15 respondents completed the final questionnaire. Since this questionnaire contained only one question, analyzing the measurement recommendations previously outlined did not seem necessary. In accordance with Alexandrov et al. (1996) and Pasukeviciute and Roe (2001), we opted for a broader definition of consensus. In line with the authors, consensus is defined as 67% agreement among experts using a nominal scale.

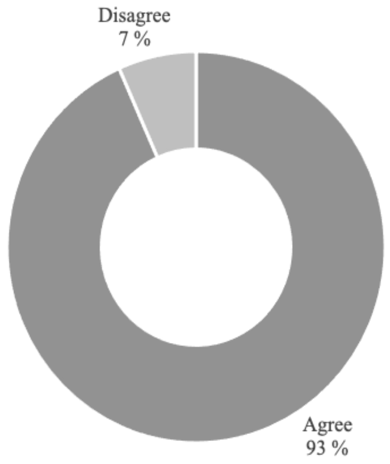
4.5.4 Findings

Out of the 15 respondents, 14 agreed with the model. In Figure 5, we present a pie chart summarizing the responses, indicating a substantial agreement of 93%, surpassing the recommended thresholds suggested by Alexandrov et al. (1996) and Pasukeviciute and Roe (2001). The remaining respondent who did not agree provided the following feedback:

"*The model appears to be designed as a diagnostic tool for consultants/advisors/researchers. It can certainly be useful for this (and for designing measures), but such models are difficult to implement internally. Should be narrowed down to external use in its current form*".

With regard to the final questionnaire, we do not consider the single disagreement to be significant. Therefore, it can be concluded that the panel reached a consensus during the final round. However, taking this feedback into consideration, we suggest future research explores this matter in greater detail.

Figure 5: *Overview of the Final Consensus, N = 15*



5.0 Discussion

This thesis attempted to explore strategies HR practitioners can employ to cope with ethical challenges associated with AI recruiting. In this case, the primary objective was to develop a comprehensive maturity model that enables professionals to address ethical concerns that have been outlined. The study identified four key areas of ethical concerns, namely privacy, AI performance, and transparency and accountability concerns, while also examining job concerns. Upon further analysis, the experts reached a consensus that job concerns were not of significant ethical concern. Consequently, our framework aims to specifically address the ethical concerns surrounding privacy, performance, and transparency and accountability in AI recruiting.

5.1 Summary of findings

Throughout the five phases of this study, 33 coping strategies were identified to mitigate the areas of ethical concerns. As a result, we have developed a maturity model referred to as CS for AIR-MM. The model encompasses five levels, each incorporating specific coping strategies that effectively cope with the identified areas of concern. Utilizing this model, organizations can facilitate continuous improvement in the ethical utilization of AI recruiting. The following will further emphasize the importance of these findings and their significance for current research in this domain.

5.1.1 Level 2: Managed

Given the regulatory framework pertaining to personal data, the General Data Protection Regulation (GDPR) assumes a critical role in overseeing the collection, storage, and processing of personal data by AI applications. (Goddard, 2017). Accordingly, our findings indicate that obtaining consent and adhering to GDPR regulations are essential to ensure legal compliance, individual control over personal data, and the preservation of data subject rights (van Ooijen & Vrabec, 2019). This aligns with the existing literature emphasizing the significance of obtaining consent for data processing within the realm of AI recruiting (Andreotta et al., 2022; Hunkenschroer & Luetge, 2022). In support of these statements, our findings indicate that providing candidates with information that aligns with GDPR guidelines can further mitigate privacy concerns, preferably in a clear, comprehensible, and transparent manner (Ufert & Fabienne, 2020; Wulf & Seizov, 2022).

Moreover, the results of our study suggest that incorporating a terms of use agreement that specify data collection and storage practices can mitigate these areas' ethical implications. Aligning with the literature, a terms of use agreement can enhance accountability and demonstrate the organization's commitment to safeguarding personal data (Steinfeld, 2016). However, these agreements, along with AI disclosures, should be designed in a format that avoids unnecessary complexity to ensure comprehension among data subjects (Wulf & Seizov, 2022).

Further, our findings state that recognizing the collected data as a candidate's property may reinforce the acknowledgment of candidates' privacy rights and foster a deeper respect for their personal data. Additionally, it was found that HR professionals should exercise control over the data accessible to AI tools to mitigate risks associated with the deployment of AI tools in recruitment. A similar conclusion was made by Janssen et al. (2020), stating that AI must be controlled in critical decision-making processes. To further address the ethical concerns surrounding privacy, we found that organizations should guarantee safe storage of data by refraining from selling or sharing it with third parties, aligning with the recommendations of Andreotta et al. (2021) and Hunkenschroer and Luetge (2022).

Moreover, current research states that while AI tools claim to reduce bias and enhance objectivity, their actual performance may deviate from these promises. It is imperative to consider the implications of AI performance to make informed decisions and address potential challenges in the implementation of AI-based recruitment systems (Hunkenschroer & Luetge, 2022). Our findings align with current research and the emerging coping strategies suggest that by employing anonymized CVs, where AI tools remove all non-relevant information, allowing assessments to focus solely on candidates' qualifications, the risk of AI bias may be minimized (Lin et al., 202; Yarger et al., 2020). As demonstrated by Amazon, biased or unrepresentative data can lead to discriminatory outcomes (Black & van Esch, 2020; Brendel et al., 2021; Ore & Sposato, 2021). To manage the effects of such biases, our findings show that it is crucial to adopt comprehensive measures to identify and eliminate potential bias in the dataset prior to training the AI model, a position supported by Tambe et al.'s (2019) arguments. Kazim et al. (2021) maintain that the greater the degree of human control over an AI process, the lower the risk. In line with this proposition, our findings state that limiting the final stages of the recruitment process to human recruiters exclusively can be a significant coping strategy. Further, our findings state that identifying job-relevant parameters and programming AI to exclusively consider these factors to avoid discriminatory behavior, are consistent with the statements made by Cheng and Hackett (2021). Moreover, our results demonstrate that HR professionals may use the tools to only meet simple requirements and handle the more complex aspects of the tasks themselves as a way of mitigating AI performance concerns. A similar conclusion was reached by Hunkenschroer and Luetge (2022), who stated that practitioners must not allow AI to have complete and sole control over hiring decisions. Another strategy practitioners may employ is continuing their usual recruiting procedures when using AI as an assisting tool, as a way of mitigating AI performance concerns. Rather than fully replacing current practices with AI, practitioners should integrate AI recruiting technologies into their existing processes.

Moreover, Black and van Esch (2020) state that AI recruiting allows personal information to be utilized or shared without a candidate's knowledge or consent, a matter of substantial concern. Our study contributes to their research by suggesting that obtaining consent before collecting data from social media and avoiding excessive inquiries will be beneficial methods to reduce such ethical concerns. Further, in line with Arnold et al. (2019) using an external third party to gain knowledge and understandability of the AI tool has been proposed to assist in strengthening HR practitioners' understanding of the tools, consequently decreasing the significant ethical concern regarding invalid and unreliable AI tools. Goretzko and Israel (2022) emphasize transparency and accountability when engaging with

AI systems. Following their statements, our findings suggest creating an agreement that ensures that all data is removed and guarantees candidates that their information will not be misused. Additionally, our findings suggest that relying on several measures in the recruitment process to detect deviations within the AI tools training, will enhance the transparency and ethical integrity of AI recruitment, in line with Hunkenschroer and Luetge (2022) assertions.

5.1.2 Level 3: Defined

Current research asserts that by implementing robust access controls to restrict data access to authorized personnel and regularly disposing of unnecessary data, including backups and copies, organizations can address the risks associated with data storage (Alkhadhr et al., 2017; Uddinn et al., 2019). Moreover, our findings state that organizations can consider adopting automated data deletion policies, as suggested by research conducted by Alkhadhr et al. (2017) and Uddinn et al. (2019). These policies involve establishing predefined timeframes for the automatic removal of data, specifically targeting candidates who do not fulfill the position requirements.

In addition to data storage concerns, there are other ethical concerns associated with AI recruiting, such as the risk of human error in AI algorithms and the potential for AI technologies to act unethically by chance. Our findings indicate that ensuring HR practitioners' understanding of psychometrics to verify AI developers' claims, plays a vital role in mitigating these concerns. This is in line with the existing literature, emphasizing the importance of practitioners obtaining critical information about the psychometric reliability of AI tools (Oswald et al., 2020; Hunkenschroer & Luetge, 2022). Consistent with the literature, our findings further suggest that HR professionals should require AI vendors to provide evidence of the validity of their AI tools to ensure their credibility and ethical use (Hunkenschroer & Luetge, 2022). Hunkenschroer and Luetge (2022) argue that human involvement in AI training and validation is crucial, which aligns with our findings indicating that practitioners can ensure the quality of AI tools by continuously comparing their results to those of human recruiters.

Moreover, our findings reveal that strengthening the training of AI tools by providing them with diverse information, similar to the training of HR practitioners, can enhance their performance and reduce the risk for hiring discrimination. This finding resonates with research conducted by Yarger et al. (2020), which proposes that organizations can promote inclusion and equity in AI by fostering diverse teams of data scientists.

In line with Rossi (2019), practitioners seeking to enhance trust in technology can achieve this by developing a comprehensive understanding of psychometrics, which enables them to evaluate the validity and reliability of measurements. To further mitigate transparency and accountability concerns, practitioners may opt to involve an unbiased third party to validate the AI tool, as suggested by Oswald et al. (2020) stating that practitioners should refer to professional test standards when assessing AI technologies.

5.1.3 Level 4: Predicable

Our research findings reinforce the importance of validating AI tools and algorithms, which is consistent with the findings in the literature (Hunkenschroer & Luetge, 2022). Consequently, the most effective coping strategy was found to be assessing the predictive validity of the AI recruiting tool. Our findings are also consistent with Fountaine et al. (2019) remarks, suggesting that using user input for continuous improvement of AI tools can be a valuable coping strategy for HR professionals. Moreover, this proposition supports our findings that AI can predict job performance when employer-defined qualifications are integrated into the AI algorithm. Additionally, in line with Roper et al. (2023) assertions, our findings state that regularly testing AI tools to detect inconsistencies or deviations may reduce discriminatory behavior in AI recruiting during the selection process. Lastly, in line with Hunkenschroer and Luetge (2022) our findings reinforce the importance of considering the predictive validity of the collected data in determining a candidate's job success, which concurs with our findings.

5.1.4 Level 5: Optimizing

Fernández-Martínez and Fernández (2020) and Lin et al. (2020) indicate that an increasing number of tasks are being carried out by algorithms, however, organizations must still depend on human recruiters to ensure data accuracy (Hunkenschroer & Luetge, 2022). Our findings suggest that ensuring data input accuracy with human verification will mitigate the ethical concerns associated with AI processes, which is in line with Faust et al. (2019) findings. Additionally, Hunkenschroer and Luetge (2022) stress the importance of obtaining validation and evidence from the AI tool developer to ensure its reliability before use. This is directly in line with our findings indicating that obtaining evidence of the AI tool's validity from its provider is a significant coping strategy. Additionally, current research indicates that autonomous AI is continuously advancing and has numerous potential applications in future devices such as autonomous operating systems (Beran, 2018). However, our findings contradict the notion of perceiving AI as an independent entity. Instead, we propose viewing AI as a tool for assistance rather than a self-sufficient tool. Moreover, to foster ongoing improvement and adaptability within the organization, it is crucial to incorporate experiential knowledge and utilize best practices for optimal coping outcomes (Curtis et al., 2001). In line with Chamorro-Premuzic et al. (2016) and Hunkenschroer and Luetge (2022) arguments, our findings support the notion that maintaining transparency in the AI recruitment process, by consistently obtaining candidates' consent for the use of AI tools, serves as a significant coping strategy. Lastly, regularly testing and researching the AI-tool before use will increase accountability and reduce transparency and accountability concerns, in keeping with Hunkenschroer and Luetge's (2022) findings.

5.2 Theoretical and practical implications

Several implications, both theoretical and practical, can be drawn from this study, particularly for today's organizations engaging in AI recruiting. This study contributes to the literature on ethical challenges in AI recruiting by developing a theoretical framework. By integrating the Evaluative Framework of Coping Mechanisms by Latack and Havlovic (1992) with the People Capability Maturity Model (P-CMM) by Curtis et al. (2001), this study offers a comprehensive and structured approach for HR professionals to cope with the ethical challenges posed by AI recruiting in the selection processes. The framework conveys the significance of problem-focused coping strategies, specifically cognitive and behavioral efforts to modify or manage the situation. Moreover, it presents a maturity model, informed by experts, that categorizes coping strategies based on their maturity level, providing a guide for organizations to optimize their ethical practices in AI recruiting. The integration of these frameworks allows for a more comprehensive understanding of the coping strategies and provides a foundation for future research on ethical AI management in recruitment.

The practical implications of this study are significant for both academics and professionals in AI recruitment. The developed model provides valuable guidance on how to cope with AI technology appropriately and ensure ethical recruitment practices. HR practitioners can utilize the framework to assess their current practices and identify areas for improvement concerning ethical coping strategies. By implementing the strategies outlined in the framework, organizations can strengthen their ethical coping of AI recruiting. Furthermore, the findings of this study can stimulate further research in the area, contributing to the ongoing discussion on ethical AI management and fostering the development of a more holistic ethical framework for managing AI recruiting. Moreover, the study contributes to the HR field by developing a comprehensive maturity model that enables HR practitioners to address ethical concerns in AI recruiting. This model is a significant strength as it fills a crucial gap in the field, offering HR practitioners a practical framework to assess ethical maturity, identify areas for improvement, and implement strategies to mitigate ethical challenges effectively.

5.3 Strengths

A significant strength of our study lies in our chosen methodology. The research adopts a multi-phase data collection process from an expert panel. This iterative approach allows for the refinement and validation of concepts, facilitating the exploration of different perspectives and reaching consensus among experts (Hartl & Hess, 2017). By utilizing the Delphi method, our study leverages the collective knowledge and expertise of the panel, resulting in robust and reliable findings. Despite our relatively small sample size of 15 experts, the multi-phase analysis strengthens our findings and enables us to produce valuable results.

5.4 Limitations

It is important to emphasize that recruitment encompasses a wide range of activities. As part of our research, we focused on the screening process of recruitment, thereby limiting our focus to a single area or dimension of the overall recruitment process.

In our study, we encountered a limitation regarding the composition of our initial respondent group, which was intended to exclusively include participants from Norway. Our initial research revealed that AI development in the Norwegian HR field was not as advanced as previously believed, which hindered the scope of our findings. To overcome this limitation, we recognized the need to expand our geographic criteria to include the US, UK, and Finland. Expanding our study to include additional countries enabled us to access a larger and more diverse pool of respondents. Nevertheless, we must recognize that despite this expansion, our final sample size remained relatively small, consisting of only 15 participants. This sample size may influence the representativeness of our research findings (Miller & Murry, 2015).

Furthermore, our sample criteria of ≥ 5 years of experience in the recruitment industry may have limited the pool of potential experts and potentially introduced a bias towards other skilled professionals. Another potential limitation arises from the rapid advancement of AI-technology. Given the dynamic character of the topic, our findings may not maintain their conclusiveness or relevance over time. This may also apply to the experience of our respondents who are no longer involved in AI recruitment but rather based their conclusions and opinions from past experiences.

Moreover, our study encountered a decrease in response rate after the two first rounds, largely due to the time-consuming character of the methodology. Although we implemented measures to mitigate this limitation, it is important to note that having consistent participation from all respondents throughout the entire process would have been ideal (Hsu & Sandford, 2007). Although our dropout rate is lower than average, a dropout of five respondents may have an adverse effect on the final results given the already limited sample size (Saunders et al., 2019). In our second phase, not all respondents participated in the interview process. Our sample may therefore be skewed. To address this limitation, we made efforts to gather an even distribution of respondents from each criteria field. Additionally, we noticed a pattern of asking leading questions and providing non-verbal cues during the first interviews, which is not recommended in a Delphi study, as this may contribute to bias or influence the respondents' opinions (Hartl & Hess, 2017; Saunders et al., 2019).

Lastly, it is important to recognize that although our study focused on how HR practitioners can handle the ethical challenges associated with AI recruiting, we did not directly measure the AI recruiting tools themselves.

5.5 Future Research Directions

Our research primarily focused on the screening process of recruitment, which represents only one aspect of the overall recruitment process. To gain a more comprehensive understanding of the ethical challenges associated with AI recruiting, future research should consider broadening the scope to include other stages such as sourcing, selection, and onboarding. Examining the entire recruitment process could provide a more holistic view of the ethical concerns and enable the development of comprehensive strategies for HR professionals.

While efforts were made to expand the geographic criteria in this study, further research should aim for a more extensive cross-cultural analysis. Investigating the ethical challenges of AI recruiting across various countries and cultural contexts would uncover unique perspectives, practices, and regulatory frameworks. By considering a broader range of cultural factors, future studies can provide valuable insights into how HR professionals can navigate ethical challenges in different cultural settings. To enhance the generalizability of research findings, future studies should also strive for a larger and more diverse sample size. This would involve recruiting participants from a wider range of industries, job levels, and organizational sizes. By including a more varied pool of respondents, researchers may capture a broader range of perspectives and experiences, leading to more robust conclusions and recommendations. Additionally, further research should explore the feedback received in our final phase, phase 4, in order to explore this matter in greater detail.

Moreover, given the rapid advancement of AI technology, conducting longitudinal studies would be valuable in identifying how ethical challenges related to AI recruiting evolve over time. By observing the trends in AI recruitment tools, practices, and regulations, researchers can assess the long-term effectiveness and adaptability of strategies employed by HR professionals. Longitudinal studies would also provide insights into emerging ethical concerns and enable proactive responses to future challenges.

While our research focused on the strategies HR practitioners can employ to cope with the ethical challenges posed by AI recruiting, there may be a need for further research that directly examines the AI recruiting tools themselves. Conducting in-depth analyses of specific AI algorithms, models, and decision-making processes could shed light on their potential biases, limitations, and ethical implications. Such research could support the development of more robust and ethically appropriate AI tools for recruitment.

Accordingly, we recommend future research to broaden the scope of research, through cross-cultural studies, expanding the sample size, engaging in longitudinal studies, and analyzing AI recruiting tools directly. These directions could provide insight to a deeper understanding of the ethical challenges inherent with AI recruiting and provide valuable insights to guide HR professionals in addressing these challenges effectively.

6.0 Conclusion

Research indicates that in a world transformed by AI, organizations are faced with numerous ethical considerations when integrating these technologies into their core operations (Charlwood & Guenole, 2022). This thesis explored strategies for HR practitioners to cope with ethical challenges in AI recruiting, identifying key areas of concern such as privacy, AI performance, and transparency and accountability concerns (Hunkenschroer & Luetge, 2022). Through the development of the CS for AIR-MM, this study provides a comprehensive framework to address these concerns and facilitate ethical AI recruiting practices. By utilizing the CS for AIR-MM, organizations can systematically assess their AI recruiting practices, identify areas of improvement, and implement appropriate measures to uphold ethical standards. The widespread adoption of AI in organizations necessitates careful consideration of the ethical implications, and the CS for AIR-MM equips HR practitioners with a valuable tool to promote ethical AI recruiting practices, ensuring responsible and ethical deployment of technology while safeguarding the well-being and rights of individuals

References

Alexandrov, A. V., Pullicino, P. M., Meslin, E. M. & Norris, J. W. (1996). Agreement on Disease-Specific Criteria for Do-Not-Resuscitate Orders in Acute Stroke. *Stroke*, *27*(2), 232–237. https://doi.org/10.1161/01.str.27.2.232

Alkhadhr, S. B. & Alkandari, M. A. (2017). Cryptography and randomization to dispose of data and boost system security. *Cogent Engineering, 4*(1), Article 1300049. https://doi.org/10.1080/23311916.2017.1300049

Altman, D. G. & Bland, J. M. (2005). Standard deviations and standard errors. *BMJ, 331*, 903–903. https://doi.org/10.1136/bmj.331.7521.903

Andreotta, A. J., Kirkham, N. & Rizzi, M. (2022). AI, big data, and the future of consent. *AI & Society, 37*(4), 1715–1728. https://doi.org/10.1007/s00146- 021-01262-5

Arnold, M., Bellamy, R. K. E., Hind, M., Houde, S., Mehta, S., Mojsilovic, A., Nair, R., Ramamurthy, K. N., Reimer, D., Olteanu, A., Piorkowski, D., Tsay, J. & Varshney, K. R. (2019). FactSheets: Increasing trust in AI services through supplier's declarations of conformity. *IBM Journal of Research and Development, 63*(4/5). https://doi.org/10.1147/JRD.2019.2942288

Barnes, S. J. & Mattsson, J. (2016). Understanding current and future issues in collaborative consumption: A four-stage Delphi study. *Technological Forecasting & Social Change, 104,* 200–211. https://doi.org/10.1016/j.techfore.2016.01.006

Becker, J., Knackstedt, R. & Pöppelbuß, J. (2009). Developing Maturity Models for IT Management. *Business & Information Systems Engineering, 1*(3), 213–222. https://doi.org/10.1007/s12599-009-0044-5

Bell, E., Bryman, A. & Harley, B. (2019). *Business research methods* (5th ed.). Oxford University Press.

Beran, O. (2018). An Attitude Towards an Artificial Soul? Responses to the “Nazi Chatbot”. *Philosophical Investigations, 41*(1), 42–69. https://doi.org/10.1111/phin.12173

Black, J.S. & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons*, *63*(2), 215–226. https://doi.org/10.1016/j.bushor.2019.12.001

Brendel, A., Mirbabaie, M., Lembcke, T.B. & Hofeditz, L. (2021). Ethical Management of Artificial Intelligence. *Sustainability*, *13*(4), Article 1974. https://doi.org/10.3390/su13041974

Budhwar, P., Malik, A., Silva, M. T. T. D. & Thevisuthan, P. (2022). Artificial intelligence - challenges and opportunities for international HRM: a review and research agenda. *International Journal of Human Resource Management, 33*(6), 1065–1097. https://doi.org/10.1080/09585192.2022.2035161

Campbell, J.L., Quincy, C., Osserman, J. & Pedersen, O. K. (2013). Coding In- depth Semistructured Interviews: Problems of Unitization and Intercoder Reliability and Agreement. *Sociological Methods & Research*, *42*(3), 294–320. https://doi.org/10.1177/0049124113500475

Chamorro-Premuzic, T., Winsborough, D., Sherman, R. A. & Hogan, R. (2016).

New Talent Signals: Shiny New Objects or a Brave New World? *Industrial and Organizational Psychology, 9*(3), 621–640. https://doi.org/10.1017/iop.2016.6

Chan, P. (2022). An Empirical Study on Data Validation Methods of Delphi and General

Consensus. *Data, 7*(2), Article 18. https://doi.org/10.3390/data7020018

Charlwood, A. & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? *Human Resource*

Management Journal, 32(4), 729–742. https://doi.org/10.1111/1748-8583.12433

Chen, H.-Y. & Boore, J. R. (2010). Translation and back-translation in qualitative nursing research: methodological review. J*ournal of Clinical Nursing, 19*(1-2), 234–239. https://doi.org/10.1111/j.1365-2702.2009.02896.x

Cheng, M. M. & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review, 31*(1) Article 100698. https://doi.org/10.1016/j.hrmr.2019.100698

Cho, S., Kim, I., Kim, J., Woo, H. & Shin, W. (2023). A Maturity Model for Trustworthy AI Software Development. *Applied Sciences, 13*(8), Article 4771. https://doi.org/10.3390/app13084771

Cooper, D.R. & Schindler, P.S. (2008). *Business Research Methods* (10th ed.). McGraw-Hill.

Curtis, W., Hefley, W. A. & Miller, S. A. (2001). *People Capability Maturity Model (P-CMM) Version 2.0.* Carnegie Mellon University. https://doi.org/10.1184/R1/6581879.v1

Dawson, C. (2007). *A practical guide to research methods* (3rd ed.). Begbroke.

Doke, E. R. & Swanson, N. E. (1995). Decision variables for selecting prototyping in information systems development: A Delphi study of MIS managers. *Information & Management, 29*(4), 173–182. https://doi.org/10.1016/0378-7206(95)00021-N

Easton, K.L., McComish, J. F. & Greenberg, R. (2000). Avoiding Common Pitfalls in Qualitative Data Collection and Transcription. *Qualitative Health Research, 10*(5), 703–707. https://doi.org/10.1177/104973200129118651

Edmonds, W. A. & Kennedy, T. D. (2017). *An applied guide to research designs : quantitative, qualitative, and mixed methods* (2nd ed.). Sage.

European Commission. (2019). *Ethics guidelines for trustworthy AI.* https://data.europa.eu/doi/10.2759/346720

Faust, O., Ciaccio, E. J., Majid, A. & Acharya, U. R. (2019). Improving the safety of atrial fibrillation monitoring systems through human verification. *Safety Science, 118*, 881–886. https://doi.org/10.1016/j.ssci.2019.05.013

Fernández-Martínez, C. & Fernández, A. (2020). AI and recruiting software: Ethical and legal implications. *Paladyn: Journal of Behavioral Robotics, 11,* 199–216. https://doi.org/10.1515/pjbr-2020-0030

Folkman, S. & Lazarus, R. S. (1980). An Analysis of Coping in a Middle-Aged Community Sample. *Journal of Health and Social Behavior*, *21*(3), 219–239. https://doi.org/10.2307/2136617

Fountaine, T., McCarthy, B. & Saleh, T. (2019). Building the AI-Powered Organization. *Harvard Business Review.* https://web-s-ebscohost-com.ezproxy.library.bi.no/ehost/pdfviewer/pdfviewer?vid=0&sid=7617d77c-9326-4413-866c-dabcb7b6ee5a%40redis

Gaudio, G. (2022). Algorithmic bosses can't lie! How to foster transparency and limit abuses of the new algorithmic managers. *Comparative Labor Law & Policy Journal, 42*(3), 707–741. https://www.proquest.com/scholarly-journals/algorithmic-bosses-cant-lie-how-foster/docview/2754073001/se-2

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *Qualitative Report*, *8*(4), 597-607. https://doi.org/10.46743/2160- 3715/2003.1870

Goddard, M. (2017). The EU General Data Protection Regulation (GDPR): European Regulation that has a Global Impact. *International Journal of Market Research, 59*(6), 703–705. https://doi.org/10.2501/IJMR-2017-050https://doi.org/10.2501/IJMR-2017-050

Goretzko, D. & Israel, L. S. F. (2022). Pitfalls of Machine Learning-Based Personnel Selection. *Journal of Personnel Psychology, 21*(1), 37–47. https://doi.org/10.1027/1866-5888/a000287

Harji, D., Griffiths, B., Velikova, G., Sagar, P. & Brown, J. (2016). Systematic review of health-related quality of life in patients undergoing pelvic exenteration. *European Journal of Surgical Oncology, 42*(8), 1132–1145. https://doi.org/10.1016/j.ejso.2016.01.007

Hartl, E. & Hess, T. (2017). The Role of Cultural Values for Digital Transformation: Insights from a Delphi Study. *23rd Americas Conference on Information System, AMCIS* 2017 (volume 2, p. 1364-1374). Association for Information Systems. https://www.researchgate.net/publication/330353915_The_Role_of_Cultural_Values_for_Digital_Transformation_Insights_from_a_Delphi_Study

Hsu, C. & Sandford, B. A. (2007). The Delphi Technique: Making Sense of Consensus. *Practical Assessment, Research and Evaluation, 12*(10). https://doi.org/10.7275/pdz9-th90

Hunkenschroer, A. & Luetge, C. (2022). Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. *Journal of Business Ethics, 178,* 977–1007. https://doi.org/10.1007/s10551-022-05049-6

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S. & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. G*overnment Information Quarterly, 37*(3), Article 101493. https://doi.org/10.1016/j.giq.2020.101493

Kallio, H., Pietilä, A.-M., Johnson, M. & Kangasniemi, M. (2016). Systematic methodological review: developing a framework for a qualitative semi- structured interview guide. *Journal of Advanced Nursing, 72*(12), 2954– 2965. https://doi.org/10.1111/jan.13031

Kaplan, J. (2022). *Artificial intelligence, business, and civilization : our fate made in machine*s. Routledge.

Kazim, E., Koshiyama, A. S., Hilliard, A. & Polle, R. (2021). Systematizing Audit in Algorithmic Recruitment. *Journal of Intelligence, 9*(3), Article 46. https://doi.org/10.3390/jintelligence9030046

Langer, M. & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior, 123*, Article 106878. https://doi.org/10.1016/j.chb.2021.106878

Latack, J.C. (1986). Coping With Job Stress: Measures and Future Directions for Scale Development. *Journal of Applied Psychology*, *71*(3), 377–385. https://doi.org/10.1037/0021-9010.71.3.377

Latack, J.C. & Havlovic, S. J. (1992). Coping with job stress: A conceptual evaluation framework for coping measures. *Journal of Organizational Behavior, 13*(5), 479–508. https://doi.org/10.1002/job.4030130505

Leutner, F. & Chamorro-Premuzic, T. (2018). Stronger Together: Personality, Intelligence, and the Assessment of Career Potential. *Journal of Intelligence, 6*(4), Article 49. https://doi.org/10.3390/jintelligence6040049

Lin, Y.-T., Hung, T.-W. & Huang, L.T.-L. (2020). Engineering equity: How AI can help reduce the harm of implicit bias. *Philosophy & Technology*, *34*, 65-90. https://doi.org/10.1007/s13347-020-00406-7

Loebbecke, C., Sawy, O. E., A., Kankanhalli, A., Markus, M. L., Te'eni, D., Wrobel, S., Rydén, P. & Obeng-Antwi, A. (2020). Artificial Intelligence Meets IS Researchers: Can It Replace Us? *Communications of the Association for Information Systems, 47*, 273-283. https://doi.org/10.17705/1CAIS.04713

Pasukeviciute, I. & Roe, M. (2001). The politics of oil in Lithuania: strategies after transition. *Energy Policy, 29*(5), 383–397. https://doi.org/10.1016/S0301-4215(00)00134-8

MacCarthy, B. L. & Atthirawong, W. (2003). Factors affecting location decisions in international operations - a Delphi study. *International Journal of Operations & Production Management, 23*(7), 794–818. https://doi.org/10.1108/01443570310481568

Merfeld, K., Wilhelms, M.-P., Henkel, S. & Kreutzer, K. (2019). Carsharing with shared autonomous vehicles: Uncovering drivers, barriers, and future developments – A four-stage Delphi study. *Technological Forecasting & Social Change, 144,* 66–81. https://doi.org/10.1016/j.techfore.2019.03.012

Miller, M. T. & Murry, J. W. Jr. (2015). Faculty Response to Department Leadership: Strategies for Creating More Supportive Academic Work Environments. *College Quarterly, 18*(4). https://files.eric.ed.gov/fulltext/EJ1095929.pdf

Okoli, C. & Pawlowski, S. D. (2004). The Delphi method as a research tool: an example, design considerations, and applications. *Information and Management, 42*(1), 15–29. https://doi.org/10.1016/j.im.2003.11.002

Ore, O. & Sposato M. (2021) Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis, 30*(6) 1771-1782. https://doi.org/10.1108/IJOA-07-2020-2291

Oswald, F. L., Behrend, T. S., Putka, D. J. & Sinar, E. (2020). Big data in industrial-organizational psychology and human resource management: Forward progress for organizational research and practice. *Annual Review of Organizational Psychology and Organizational Behavior, 7,* 505–533. https://doi.org/10.1146/annurev-orgpsych-032117-104553

Powell, C. (2003). The Delphi technique: myths and realities. *Journal of Advanced Nursing, 41*(4), 376–382. https://doi.org/10.1046/j.1365- 2648.2003.02537.x

Roper, J., Lin, M. & Rong, Y. (2023). Extensive upfront validation and testing are needed prior to the clinical implementation of AI-based auto- segmentation tools. *Journal of Applied Clinical Medical Physics, 24*(1), Article e13873). https://doi.org/10.1002/acm2.13873

Rossi, F. (2018). Building trust in artificial intelligence. *Journal of International Affairs, 72*(1), 127–134. https://www.jstor.org/stable/26588348

Saldaña, J. (2020). Qualitative Data Analysis Strategies. In P. Leavy (Ed.), The Oxford Handbook of Qualitative Research (2nd ed., p. 876-911). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190847388.013.33

Saunders, M. N. K., Lewis, P. & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Pearson.

Sandelowski, M., Barroso, J. & Voils, C. I. (2007). Using qualitative metasummary to synthesize qualitative and quantitative descriptive findings. *Research in Nursing & Health, 30*(1), 99–111. https://doi.org/10.1002/nur.20176

Steinfeld, N. (2016). "I agree to the terms and conditions": (How) do users read privacy policies online? An eye-tracking experiment. *Computers in Human Behavior, 55*, 992–1000. https://doi.org/10.1016/j.chb.2015.09.038

Tambe, P., Cappelli, P. & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review, 61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Tersine, R. & Riggs, W. E. (1976). The Delphi technique: A long-range planning tool. *Business Horizons, 19*(2), 51–56. https://doi.org/10.1016/0007-6813(76)90081-1https://doi.org/10.1016/0007-6813(76)90081-1

Ufert, F. (2020). AI Regulation Through the Lens of Fundamental Rights: How Well Does the GDPR Address the Challenges Posed by AI? *European Papers*, *5*(2), 1087–1097. https://doi.org/10.15166/2499-8249/394

Uddin, M., Islam, S. & Al-Nemrat, A. (2019). A Dynamic Access Control Model Using Authorising Workflow and Task-Role-Based Access Control. *IEEE Access*, *7*, 166676–166689. https://doi.org/10.1109/ACCESS.2019.2947377

van Ooijen, I. & Vrabec, H. U. (2019). Does the GDPR Enhance Consumers' Control over Personal Data? An Analysis from a Behavioral Perspective. *Journal of Consumer Policy, 42*(1), 91–107. https://doi.org/10.1007/s10603-018-9399-7

Warner, W. J. & Washburn, S. G. (2009). Issues facing urban agriscience teachers: A Delphi study. *Journal of Agricultural Education, 50*(1), 105–115. https://doi.org/10.5032/jae.2009.01105

Williamson, K. (2002). *Research methods for students, academics, and professionals: Information management and systems* (2nd ed.). Elsevier.

Winkler, J. & Moser, R. (2016). Biases in future-oriented Delphi studies: A cognitive perspective. *Technological Forecasting & Social Change, 105*, 63–76. https://doi.org/10.1016/j.techfore.2016.01.021

Wulf, A. J. & Seizov, O. (2022). Please understand we cannot provide further information: evaluating content and transparency of GDPR-mandated AI disclosures. *AI & Society*. https://doi.org/10.1007/s00146-022-01424-z

Wright, G., Lawrence, M.J. & Collopy, F. (1996). The role and validity of judgment in forecasting. *International Journal of Forecasting, 12*(1), 1–8. https://doi.org/10.1016/0169-2070(96)00674-7

Yarger, L., Cobb-Payton, F. & Neupane, B. (2020). Algorithmic equity in the hiring of underrepresented IT job candidates.

Online Information Review, 44, 383–395. https://doi.org/10.1108/OIR-10-2018-0334

Zhang, H., Zhan, T. & Davidson, I. (2021). A Self-Supervised Deep Learning Framework for Unsupervised Few-Shot Learning and Clustering. *Pattern Recognition Letters, 148,* 75–81. https://doi.org/10.1016/j.patrec.2021.05.004

Appendix

Appendix 1. Information Letter & Consent Form

Are you interested in taking part in the research project

"Tackling Ethical Management of AI in Recruitment"?

Purpose of the project
You are invited to participate in our research project. The research project is carried out as part of our master's degree at BI Norwegian Business School and will be submitted as our master's thesis at graduation. The purpose of the research project is to examine the role of artificial intelligence in recruitment processes and the ethical challenges it poses for HR managers. The research question to be analysed is "How can HR managers cope with ethical challenges with AI during recruitment processes?"». The research project will be carried out using a Delphi study where there will be four survey rounds, each lasting of approx. 10 minutes, and one optional interview of approx. 30-45 minutes. We will carry out the surveys and the interview in the period between the beginning of February and the beginning of April. As a participant, you will have five days from the publication date to answer the questionnaires. We will operate with a 9-day interval before the next round is sent out.

Current dates for the surveys:

- round one: 6-10 February
- round two: 20-24 February (interview)
- round three: 6-10 March
- round four: 20-24 March,
- round five (Back-up round): 3-5 April.

The information will not be used for other purposes, e.g., teaching, or other research projects.

Which institution is responsible for the research project?
BI Norwegian Business School is responsible for the project (data controller).

Why are you being asked to participate?
The sample selection is drawn using various selection criteria. The project's selection criteria include that the person concerned must either be in a high-ranking position in an organisation, work in recruitment or work in academia. The sample must contribute by providing valuable insight in HR, artificial intelligence (AI) or ethics, and should therefore possess relevant knowledge and experience in at least one of these areas. We have further developed the selection criteria to include professionals who work in AI or HR as consultants or advisors.

We are asking you to participate in this subject project as we believe you possess the right knowledge and relevant experience to provide valuable and important information to be able to help answer to our research question.

What does participation involve for you?
If you choose to participate in the project, it will require you fill out 4 to 5 questionnaires. It will take you approx. 10 minutes per questionnaire. The questionnaire will be sent at 9-day intervals. The questionnaire contains questions about privacy concerns, performance concerns – both reliability and bias-related, transparency and morality concerns, and job security. All groups will receive equal

treatment and identical questionnaire. Your answers from the questionnaire are registered electronically through the software "Qualtrics". The questionnaire will be anonymous, and no personal information will be collected during the questionnaire.

If you choose to participate in round two (the interview), this means that an audio recording and/or notes from the interview will be taken. The notes and/or audio recording will be stored in a password-protected file and no personal information will be collected.

Your participation is scheduled to end on 5. April 2023.

Participation is voluntary
Participation in the project is voluntary. If you chose to participate, you can withdraw your consent at any time without giving a reason. All information about you will then be made anonymous. There will be no negative consequences for you if you chose not to participate or later decide to withdraw.

Your personal privacy – how we will store and use your personal data
We will only use your personal data for the purpose(s) specified here and we will process your personal data in accordance with data protection legislation (the GDPR).

- Annika Haight, Elizabeth Johnson, and our supervisor Elizabeth Solberg will have access to the information.
- We will replace your name and contact details with a code that is stored on a separate name list separate from other data. The data material will also be locked and encrypted on only Annika Haight and Elizabeth Johnson's computers. All collected data will be deleted at (1) the end of participation, and/or (2) at the end of the research project.
- The participants will not be able to be recognized in any publication of the thesis. Only the selection criteria will be mentioned in the master's thesis.

What will happen to your personal data at the end of the research project?
The project is scheduled to be submitted on 7 July 2023. The project end date is 3 weeks after submission. All the collected data, including any digital recordings, will be deleted at the end of the project.

Your rights
So long as you can be identified in the collected data, you have the right to:

- access the personal data that is being processed about you
- request that your personal data is deleted
- request that incorrect personal data about you is corrected/rectified
- receive a copy of your personal data (data portability), and
- send a complaint to the Norwegian Data Protection Authority regarding the processing of your personal data

What gives us the right to process your personal data?
We will process your personal data based on your consent.

Based on an agreement with BI Norwegian Business School, The Data Protection Services of Sikt – Norwegian Agency for Shared Services in Education and Research has assessed that the processing of personal data in this project meets requirements in data protection legislation.

Where can I find out more?
If you have questions about the project, or want to exercise your rights, contact:

- *Elizabeth Johnson, student at* BI Norwegian Business School, elisolveig@hotmail.com
- *Annika Haight, student at* BI Norwegian Business School, Annikahaight@outlook.com
- *Supervisor: Elizabeth Solberg at* BI Norwegian Business School, elizabeth.solberg@bi.no
- *Our Data Protection Officer: Vibeke Nesbakken, personvernombud@bi.no. Please send confidential and sensitive personal information by post to BI Norwegian Business School, Nydalsveien 37, 0484 OSLO v/Personvernombudet.*

If you have questions about how data protection has been assessed in this project by Sikt, contact:

- email: (personverntjenester@sikt.no) or by telephone: +47 73 98 40 40.

Yours sincerely,

Elizabeth Solberg	Annika Haight	Elizabeth Johnson
(Supervisor)	(Student)	(Student)

Consent form

I have received and understood information about the project "Tackling Ethical Management of AI in Recruitment" and have been given the opportunity to ask questions. I give consent:

- ☐ to participate in questionnaires
- ☐ to participate in an interview (round 2)

I give consent for my personal data to be processed until the end of the project.

(Signed by participant, date)

Appendix 2. Phase one - Questionnaire

Round one – Questionnaire phase one

Start of Block: Block 4

This questionnaire addresses different ethical challenges or situations that could give cause for professional concern when using artificial intelligence (AI) in recruitment practices. The statements that follow list several possible professional concerns regarding the use of AI in recruitment practices. This questionnaire has a total of 15 questions divided into four areas - privacy concerns, performance concerns, transparency & accountability concerns, and job concerns.

You will be able to select several boxes, however we prefer you to only select one. If you would like to comment on a statement or provide an in-depth answer, please use the optional "comment" box as well as selecting a number. Please indicate on a scale of 1 (low) to 5 (high) the extent to which you are concerned about each topic.

It will take you approximately 10 minutes to complete. Please continue when ready.

Page Break

End of Block: Block 4

Start of Block: Privacy concerns

Privacy concerns

Please indicate on a scale of 1-5 the extent to which you are concerned about each ***(1 = low concern; 5 = high concern)***.

I have:

Q1 Concerns about collecting data about job candidates through third parties (i.e., via data obtained from businesses with no direct connection to candidates)

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

Q2 Concerns about who owns the data (e.g., the firm using the AI tool or the AI developer)

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

Q3 Concerns about storing candidate data derived from AI recruitment practices

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

Q4 Concerns about the process of obtaining the job applicant's consent to use AI to evaluate them as a job candidate

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

End of Block: Privacy concerns

Start of Block: Performance

Performance concerns
I have:

Q5 Concerns about if AI used in recruitment practices accurately measure factors that predict future job performance

- [ ] 1 -Low concerns
- [ ] 2 - Mild concerns
- [ ] 3 - Neutral
- [ ] 4 - Concerns
- [ ] 5 - High concerns
- [ ] Comment ____

Q6 Concerns about if AI used in recruitment practices contributes to hiring discrimination

- [ ] 1 - Low concerns
- [ ] 2 - Mild concerns
- [ ] 3 - Neutral
- [ ] 4 - Concerns
- [ ] 5 - High concerns
- [ ] Comment ____

Q7 Concerns about if AI used in recruitment practices are valid and reliable

- 1 - Low concerns
- 2 - Mild concerns
- 3 - Neutral
- 4 - Concerns
- 5 - High concerns
- Comment ____

End of Block: Performance

Start of Block: Transparency & accountability concerns

<u>Transparency & accountability concerns</u>
I have:

Q8 Concerns about the understandability of how the AI works (i.e., its process for generating results)

- 1 - Low concerns
- 2 - Mild concerns
- 3 - Neutral
- 4 - Concerns
- 5 - High concerns
- Comment ____

Q9 Concerns about the openness and transparency between employers and job candidates about how AI is used in the selection process

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

Q10 Concerns about whether the emotional complexities and psychological aspects of screening candidates are better handled by humans than AI

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

Q11 Concerns about the trust placed in the accuracy of AI

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

Q12 Concerns about collecting data from the job candidate's social media accounts

- ☐ 1 - Low concerns
- ☐ 2 - Mild concerns
- ☐ 3 - Neutral
- ☐ 4 - Concerns
- ☐ 5 - High concerns
- ☐ Comment ____

End of Block: Transparency & accountability concerns

Start of Block: Job concerns

Job concerns
I have:

Q13 Concerns that AI used in recruitment practices could cause a threat to the employment of human recruiters

- [ ] 1 - Low concerns
- [ ] 2 - Mild concerns
- [ ] 3 - Neutral
- [ ] 4 - Concerns
- [ ] 5 - High concerns
- [ ] Comment ____

Q14 Concerns that AI used in recruitment practices does not actually help company personnel carry out recruitment related activities

- [ ] 1 - Low concerns
- [ ] 2 - Mild concerns
- [ ] 3 - Neutral
- [ ] 4 - Concerns
- [ ] 5 - High concerns
- [ ] Comment ____

Q15 Concerns that using AI in recruitment practices could lead to over surveillance of human recruiters or other personnel working with the AI

- ▢ 1 - Low concerns
- ▢ 2 - Mild concerns
- ▢ 3 - Neutral
- ▢ 4 - Concerns
- ▢ 5 - High concerns
- ▢ Comment ____

End of Block: Job concerns

Start of Block: Block 5

Q22 In what field to you work?

- ○ HR
- ○ AI
- ○ Academia
- ○ Other
- ○ Do not wish to answer

End of Block: Block 5

Appendix 3. Phase two - Interview guide

Phase 2 – Interview guide

Transparency and accountability concerns

1. In your opinion, how should recruiters and organizations ensure that their AI tools (in recruitment practices) are gathering data ethically when collecting data from candidates' social media accounts?
2. What measures should HR professionals take to increase the understandability of AI?
3. Is there a way to ensure transparency between employer and candidate? If so, how can this be done?
4. Do you have any suggestions as to how to increase the level of trust individuals place in AI's accuracy?
5. How will you ensure that the emotional complexities and psychological aspects of screening candidates will be addressed when using AI tools in recruiting?

Performance

6. How should practitioners/companies ensure that AI tools are valid and reliable?
7. What measures do you think are necessary to take in order to ensure that the AI tools accurately measure future job performance of a candidate?
8. How should recruiters ensure that AI recruiting does not contribute to hiring discrimination?

Privacy (2.5)

9. How do you ensure that your tools ensure ethical data collection through third parties?
10. How do you store the data collected by AI tools?
11. Who owns the data collected?
12. How do you obtain consent from job applicants to the use of AI in your recruitment process?

Page 1 of 1

Appendix 4. Phase three - Questionnaire

Round 3 – Questionnaire for phase 3

Start of Block: Block 14

This questionnaire addresses different strategies that can be used to cope with the ethical challenges that can be caused by the use of AI in recruitment practices. The coping strategies involve different ways of mitigating or dealing with ethical concerns.

Please indicate how much you agree with the strategy you feel best addresses the ethical challenge, where *1 = strongly disagree* and *5 = strongly agree*. If you would like to comment on a statement, please use the optional comment box.

It will take you approximately 10 minutes to complete. It will be recommended to use a computer to answer this questionnaire. Please continue when ready.

End of Block: Block 14

Start of Block: SoMe

Using AI tools to collect data through social media (SoMe)

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q1 **When collecting candidate social media data using AI tools:**

	1 - strongly disagree (1)	2 (2)	3 (3)	4 (4)	5 - strongly agree (5)
I believe the candidates have a responsibility for what they put online. I am therefore free to collect this data (1)	○	○	○	○	○
I prefer to not use AI when collecting data from SoMe (2)	○	○	○	○	○
I believe it is the employer's responsibility to avoid excessive inquiries (3)	○	○	○	○	○
I believe that as long as I do not save the data until I have contacted the candidate, I am free to use it (4)	○	○	○	○	○
I believe that using AI does not introduce other ethical considerations compared to doing it myself (5)	○	○	○	○	○

Q3 **It is important that the employer considers these aspects when collecting data from a candidate's SoMe profile using AI tools:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
The accuracy in which the collected data can predict a candidate's job success (1)	○	○	○	○	○
Obtaining consent from the candidate before collecting their SoMe data (2)	○	○	○	○	○
Ensuring the predictive validity of the AI tool (3)	○	○	○	○	○

Q4 **In my opinion, when using AI tools in recruitment:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
I do not see any problems with collecting the data through SoMe so long as it is public information (1)	○	○	○	○	○
I do not see any problems with collecting data through SoMe as long as I do not store it (2)	○	○	○	○	○
I do not see any problems with collecting data through SoMe as long as the AI tools do not collect more data than what a human recruiter could do (3)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: SoMe

Start of Block: Valid

Valid and reliable practices when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q5 **Valid and reliable practices with the use of AI tools in recruitment can be ensured by developers through:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Ensuring thorough research into the validity of the AI tools (1)	○	○	○	○	○
Continuously improving the AI tools through user/client input (2)	○	○	○	○	○
Providing evidence of the AI tools validity (3)	○	○	○	○	○

Q6 **Valid and reliable practices with the use of AI in recruitment processes can be ensured by employers through:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Checking the quality of the AI tools by continuously comparing their results to those of human recruiters (1)	o	o	o	o	o
Assuring that employers understand the psychometrics of the AI tools in order to verify that what the developers claim is accurate (2)	o	o	o	o	o
I believe the AI tools are trustworthy, so there is no need to further validate them (3)	o	o	o	o	o
Using the tools only to meet simple requirements and handling the more complex aspects of the task myself (4)	o	o	o	o	o
Using an unbiased third party to validate the AI tool (7)	o	o	o	o	o

Making sure that data input is accurate by human verification (8)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Valid

Start of Block: Job performance

The accuracy of predicting job performance with AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q7 **In my opinion:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
I believe that AI tools cannot predict job performance (1)	○	○	○	○	○
AI tools can predict job performance if an employer identifies the qualifications required to succeed in a position and incorporates these into the AI algorithm (2)	○	○	○	○	○
I believe AI tools can predict job performance without the help of the employer (3)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Job performance

Start of Block: Discrimination

Hiring discrimination when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q8 **To avoid hiring discrimination when using AI tools in recruitment processes, employers should:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Maintain their usual operating procedures when using AI tools (1)	○	○	○	○	○
Conduct the final stages of the recruitment process with human recruiters only (2)	○	○	○	○	○
View AI as a tool for assistance rather than a self-sufficient tool (3)	○	○	○	○	○
Do nothing - AI tools are less discriminatory than human recruiters (4)	○	○	○	○	○

Q9 **I believe that the following could reduce the discriminatory behavior of the AI tools:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Obtaining evidence of the AI tools validity (1)	○	○	○	○	○
Using anonymized CVs, where the AI tools remove all non-relevant information, and allows assessments to focus solely on the candidates' qualifications (2)	○	○	○	○	○
Ensuring that the AI tools are equipped with all the necessary data (3)	○	○	○	○	○

Q10 **I believe that:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Providing AI tools with diverse information, similar to how HR personnel are trained, will reduce discriminatory behavior in AI (1)	○	○	○	○	○
By identifying the relevant parameters for the job and programming AI to look for only these parameters, we can reduce discriminatory behavior in AI (2)	○	○	○	○	○
Regularly testing the tools to detect any inconsistencies or deviations, will reduce discriminatory behavior in AI (3)	○	○	○	○	○
AI is more discriminatory than human recruiters (4)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Discrimination

Start of Block: Understandability

The understandability of AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q11 **To increase the understandability of AI tools used in recruitment processes, employers can:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Gain an understanding of psychometrics to be able to evaluate the measure and its liability and validity (1)	○	○	○	○	○
Use a third party to gain knowledge and understandability (2)	○	○	○	○	○
In my opinion, employers are not required to understand how AI tools operate (3)	○	○	○	○	○
Avoid using technologically complex recruitment systems, in order to avoid losing potential candidates (4)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Understandability

Start of Block: Block 5

Transparency between employer and candidate when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q12 **To increase transparency surrounding the use of AI tools in recruitment I believe:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
One could openly and honestly disclose the use of AI tools with the candidates through a disclaimer (1)	○	○	○	○	○
One could request consent from the candidate before using AI tools in the recruitment process (2)	○	○	○	○	○
There is limited need for transparency due to the potential impact it may have on the candidate's participation in the recruiting process (3)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Block 5

Start of Block: Trust

Trust in AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q13 **In order to increase the level of trust placed in AI tools by employers and candidates, the following steps could be taken:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
One could rely on several steps in the recruitment process to detect deviations within the AI tools (1)	○	○	○	○	○
Create an agreement that ensures that all data is removed and that candidates have a guarantee that the information will not be misused (2)	○	○	○	○	○
Make sure to test and research the AI tool before use (3)	○	○	○	○	○
Assure that the AI tools are only used as a means of assisting HR consultants rather than replacing them (4)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Trust

Start of Block: Ownership

Ownership over candidate data when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q14 **I believe that one can cope with the uncertainty of data ownership when using AI tools in recruitment:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Through obtaining consent and outlining the terms of use regarding ownership of data (1)	○	○	○	○	○
Through assuming that the collector (employer) owns the data (2)	○	○	○	○	○
Through assuming that the data is the property of the source (candidate), which I am merely borrowing (3)	○	○	○	○	○
Through following the GDPR legislation, that is all that is required (4)	○	○	○	○	○
Through following the GDPR legislation and other data processing requirements (5)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Ownership

Start of Block: Collection - third parties

Data collection through third parties when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q15 **Ethical data collection through third parties with the use of AI tools, can be done through:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Following GDPR guidelines (1)	○	○	○	○	○
Making sure the employer has control over legislations and handles the data collection responsibly (2)	○	○	○	○	○
Having control over what data the AI tool has access to (3)	○	○	○	○	○
The belief that what is available online is available and free to use. Thus, the employer should not have to take any further steps (4)	○	○	○	○	○
The belief that when candidates open their profiles, they consent to the sharing of their personal information (5)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Collection - third parties

Start of Block: Storage

Storing candidate data when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q16 **I believe that one can manage storing candidate data when using AI tools in recruitment ethically by:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Only store data gathered from open sources (1)	○	○	○	○	○
Providing candidates information that is in accordance with GDPR (2)	○	○	○	○	○
Utilize terms of service to obtain consent (3)	○	○	○	○	○
Safe storage by not selling nor sharing the data to other parties (4)	○	○	○	○	○
Storing data anonymously (5)	○	○	○	○	○
Providing an automated deletion function for candidates (6)	○	○	○	○	○
As long as the purpose for saving the data is to offer the candidate the job, there is no need for additional measures (7)	○	○	○	○	○

Data storage is not a major concern (8)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Storage

Start of Block: Consent

Obtaining the job applicant's consent when using AI tools

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q17 **In order to obtain candidate consent regarding the use of AI tools in recruitment, my preferred method would be to:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Just ask them, if they say no, they will still be evaluated without the use of AI tools (1)	○	○	○	○	○
Demand consent, where the candidate will no longer be evaluated if they do not agree (2)	○	○	○	○	○
Through a terms of use agreement (3)	○	○	○	○	○
None - there is no need for excessive consent when using AI tools in the recruitment process (4)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Consent

Start of Block: Helpful tool

AI is not really a helpful tool

Please indicate your level of agreement with the following statements, where 1 = strongly disagree and 5 = strongly agree

Q18 **To ensure that AI is a helpful tool:**

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
I would use it only for administrative tasks that do not require much thought (1)	○	○	○	○	○
I would make sure to only use it as an assisting tool and not a self-sufficient resource (2)	○	○	○	○	○
I would only use AI tools for time-sensitive tasks (3)	○	○	○	○	○
I do not believe that AI tools can be made useful in recruitment (4)	○	○	○	○	○

If you would like to comment on the topic, you may do so here:

____

End of Block: Helpful tool

Start of Block: Block 13

Q19 In what field do you work?

- ○ Academia (1)
- ○ HR (2)
- ○ AI (3)
- ○ Other (4)
- ○ I prefer not to say (5)

End of Block: Block 13

Appendix 5. Phase four - Questionnaire

Round 4 - Consensus

Start of Block: Information 1

We would like to thank you for your valuable contribution to our thesis. Your involvement greatly helped us develop and refine the final model. This last questionnaire aims to determine if you agree with the model, which has been constructed based on the study findings.

The questionnaire consists of *only one* question. The following page will delve deeper into the definitions used in the model. We kindly request you to carefully read through it to ensure a clear understanding of the terms involved.

Your feedback will help validate and improve the model.
Thank you!

End of Block: Information 1

Start of Block: Information 2

Info Maturity models have been proven to be a valuable instrument for improving organizational positioning and providing improved solutions for transformation. Based on our findings of common AI concerns and their corresponding coping strategies, we propose a Coping Strategies for AI Recruitment Maturity Model (CS for AIR-MM). This maturity model shows how an organization or individual can ensure effective and reliable AI coping strategies.

Defining terms:
Level 1 - Initial: Coping strategies for AI-driven recruitment are sporadic and reactive. There is no structured approach or established methodologies, and coping relies heavily on individual efforts and skills.

Level 2 - managed: Coping strategies incorporate basic practices to handle AI-driven recruitment. Processes are documented and defined, allowing for better planning, tracking, and control of AI-driven recruitment efforts.

Level 3 - Defined: Coping strategies are well-defined, standardized, and documented. The organization or individual establishes clear coping approaches, follows established procedures, and utilizes effective coping roles and responsibilities specific to AI-driven recruitment.

Level 4 - Predictable: The strategies are data-driven and focused on optimizing AI-driven recruitment outcomes. The organization or individual collects and analyzes relevant data to measure and control coping performance, ensuring consistency, and continually improving

Page 1 of 2

coping techniques.

Level 5 - Optimized: The organization is proactive in seeking process improvement opportunities. Continuous improvement and adaptation are embedded within the coping culture, incorporating learnings from experiences and leveraging best practices to achieve superior coping outcomes.

Behavioral control: Taking proactive actions or actively participating to modify or manage the situation.
Behavioral escape: Avoiding the situation or not becoming overly concerned with the issue.
Cognitive control: Using self-talk and mental planning to take a proactive stance or engage in positive thinking to modify or manage the situation.
Cognitive escape: Using cognitive strategies such as self-talk and mental planning to avoid becoming overly concerned about the issue.

End of Block: Information 2

Start of Block: Block 2

We highly value your opinion on this model. If you are in complete agreement, simply clicking on "I Agree" will suffice. If you wish to organize the coping strategies into different levels, we welcome any suggestions.

Please click on the link to see the full-size model:
Coping strategies for AI recruitment model

Q1 Coping Strategies for AI Recruitment Maturity Model (CS for AIR-MM)

- ○ I agree with the model (1)
- ○ I do not agree with the model - (Please suggest an alternative categorization below.) (2) ____

End of Block: Block 2

Appendix 6. The 66 identified coping strategies.

Overview of the 66 Coping Strategies

Item	Coping Strategy	Ethical Area of Concern
1	I believe the candidates have a responsibility for what they put online. I am therefore free to collect this data	**Transparency/ accountability**
2	I prefer to not use AI when collecting data from social media.	*Social Media*
3	I believe it is the employer's responsibility to avoid excessive inquiries	
4	I believe that as long as I do not save the data until I have contacted the candidate, I am free to use it	
5	I believe that using AI does not introduce other ethical considerations compared to doing it myself	
6	The accuracy in which the collected data can predict a candidate's job success	
7	Obtaining consent from the candidate before collecting their social media data	
8	Ensuring the predictive validity of the AI tool	
9	I do not see any problems with collecting the data so long as it is public information	
10	I do not see any problems with collecting data as long as it is not saved	
11	I do not see any problems with collecting data as long as the AI tools do not collect more data than what a human recruiter could do	
12	Ensuring thorough research into the validity of the tool (from the developer's side)	**Performance**
13	Continuously improving the AI through user/client input.	*Valid and reliable practices*
14	Providing evidence of the tool's validity.	
15	Checking the quality of the tools by continuously comparing their results to those of human recruiters	
16	Assuring that employers understand psychometrics in order to verify that what the developers claim is accurate	
17	The AI tools are trustworthy, so there is no need to further validate them	
18	Using the tools only to meet simple requirements and handling the more complex aspects of the task myself	
19	Using a unbiased third party to validate the AI tool	
20	Making sure that data input is accurate by human verification	
21	I believe that AI cannot predict job performance	*Accuracy of job performance*
22	AI can predict job performance if an employer identifies the qualifications required to succeed in a position and incorporates these into the AI algorithm	
23	I believe AI can predict job performance without the help of the employer	
24	Maintain their usual operating procedures when using AI	*Hiring discrimination*
25	Conduct the final stage of the recruitment process with human recruiters only	
26	View AI as a tool for assistance rather than a self-sufficient tool	
27	Do nothing - AI tools are less discriminatory than human recruiters	
28	Obtaining evidence of the tool's validity	
29	Using anonymized CVs, where the AI tools remove all non-relevant information, and allows assessments to focus solely on the candidates' qualifications	
30	Ensuring that the AI tools are equipped with all the necessary data	
31	Providing AI tools with diverse information, similar to how HR personnel are trained, will reduce discriminatory behavior in AI	
32	By identifying the relevant parameters for the job and programming AI to look for only these parameters, we can reduce discriminatory behavior in AI	
33	Regularly testing the tools to detect any inconsistencies or deviations, will reduce discriminatory behavior in AI	
34	AI is more discriminatory than human recruiters	
35	Gain an understanding of psychometrics to be able to evaluate the measure and its liability and validity	**Transparency & accountability**
36	Use a third party to gain knowledge and understandability.	*Understandability*
37	In my opinion, employers are not required to understand how AI tools operate	
38	Avoid using technologically complex recruitment systems, in order to avoid losing potential candidates	
39	One could openly and honestly disclose the use of AI tools with the candidates through a disclaimer in advance	*Transparency*
40	One could request consent from the candidate to use AI tools in the recruitment process	
41	There is limited need for transparency due to the potential impact it may have on the candidate's participation in the recruiting process	
42	One could rely on several steps in the recruitment process to avoid deviations within the AI tools	*Trust*
43	Create an agreement that ensures that all data is removed and that candidates have a guarantee that the information will not be misused	
44	Make sure to test and research the tool before use	
45	Through obtaining consent and outlining the terms of use regarding ownership of data	**Privacy**
46	Through assuming that the collector (employer) owns the data	*Ownership*
47	Through assuming that the data is the property of the source (candidate), which I am merely borrowing	
48	Through following the GDPR legislation, that is all that is required	
49	Through following the GDPR legislation and other data processing requirements	
50	Following GDPR	*Data through third parties*
51	Making sure the employer has control over legislations and handles the data collection responsibly	
52	Having control over what data the AI tool has access to	
53	The belief that what is available online is available and free to use. Thus, the employer should not have to take any further steps	

54	The belief that when candidates open their profiles, they consent to the sharing of their personal information	
55	Only store data gathered from open sources	*Data storage*
56	Providing candidates information that is in accordance with GDPR	
57	Utilize terms of service to obtain consent	
58	Safe storage by not selling nor sharing the data to other parties	
59	Storing data anonymously	
60	Providing an automated deletion function for candidates who do not qualify for the position	
61	As long as the purpose for saving the data is to offer the candidate the job, there is no need for additional measures	
62	Data storage is not a major concern	
63	Just ask them, if they say no, they will still be evaluated without the use of AI	*Obtaining consent*
64	Demanding consent, where the candidate will no longer be evaluated if they do not agree	
65	Through a terms of use agreement	
66	None - there is no need for excessive consent when using AI measures in the recruitment process	

Note. Main themes are split up due to the division into sub themes.