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Ethical Concerns Upon Artificial Intelligence Empowered Human Resource Management: A Qualitative Study Among Middle-Level Managers From Beijing Technology Companies

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Abstract

The evolution of artificial intelligence (AI) in organizational management has significantly enhanced operational efficiency. However, it has introduced ethical challenges in human resource management. Between January to March 2024, this study conducted 21 semi-structured interviews with middle-level managers from high-tech companies in Beijing. Through word frequency analysis, the study found that key topics among the managers were "company," "data," "system," and "problem," with "AI" frequently recurring in the discussions. Sentiment analysis revealed generally favorable attitudes toward AI in human resource management (AI-HRM), along with nuanced emotional expressions such as inquiry, introspection, recommendation, challenge, adaptation, resistance, and indifference. The sentiment distribution of keywords aligned with topic trends. Thematic analysis identified key ethical concerns in AI-HRM, including issues related to data collection and utilization, human versus machine decision-making, quantitative versus qualitative assessment methodologies, the balance between fairness and efficiency, the need for trustworthy, explainable, and transparent AI, and the oversight of AI-HRM. This study contributes to the ethical investigation of AI-HRM from the perspective of middle-level managers, highlighting themes that are critical for understanding the theory, application, and future development of AI-HRM.

Keywords: Artificial Intelligence, Human Resources Management, Ethical Issues, Word Frequency, Word Sentiment

Introduction

Artificial Intelligence (AI) is recognized as the forefront of computational advancement closely aligned with human intelligence, particularly in addressing increasingly complex decision-making challenges (Berente et al., 2021). The notion of technological unemployment, firstly introduced by John Keynes in the 1930s, emphasizes the tension between human labor and technological automation. Studies express concerns about the potential reduction in employment opportunities due to automation (Kaplan & Haenlein, 2020). Similar to historical debates surrounding the introduction of the steam engine during the early stages of industrialization, technological advancements, including the introduction of Artificial

Intelligence, have historically displaced certain jobs while concurrently creating new employment opportunities, thereby fundamentally reshaping the division of labor (Atack et al., 2019).

There is a growing interest in studying AI applications within organization management (Budhwar et al., 2022), a trend is particularly evident in China (Peng, 2023), with an increasing number of high-tech companies exploring AI-powered technologies in HRM (Zwetsloot, 2020), and an increased number of high-tech companies are attempting to use AI-empowered technologies in HRM (Peng, 2023). However, previous studies have identified several influential factors that negatively impact firms' receptiveness to AI in management, including ethical concerns regarding decision-making systems (Barredo Arrieta et al., 2020). For instance, explainability becomes a critical issue when organizations consider implementing cutting-edge algorithms in management (Tambe et al., 2019). Moreover, the transparency of outputs generated by AI-based technologies is often questioned by general employees (Budhwar et al., 2022). On the other hand, there are also drivers of AI acceptance. AI in HRM is seen as a sophisticated tool that elevates HRM to more advanced management systems, thereby improving organizational performance (Cheng & Hackett, 2021). For instance, AI-driven screening processes can expand the candidate pool by offering opportunities to previously excluded applicants (Li et al., 2021). Additionally, AI-powered systems are believed to free HR practitioners from mundane and repetitive tasks, allowing them to focus on more meaningful work (Tambe et al., 2019).

While existing literature attempts to link Human Resource Management (HRM) with AI technology in China, covering the trajectory from AI deployment to its applications across various HRM sectors—such as human resource planning, recruitment (Zhang et al., 2023), strategic human resource management, and employee well-being (Huangshi et al., 2022), —there has been scant attention paid to how managers perceive ethical concerns related to AI-HRM. This study aims to investigate the ethical considerations of middle-level managers regarding AI-HRM.

Focusing on organizational human resource management, this study raises several unresolved ethical questions regarding AI-HRM. First, what are the general attitudes toward AI-HRM? Second, can AI-HRM achieve full acceptance from middle-level managers? Third, regarding ethical concerns, how do managers perceive the data collection and usage processes involved in AI-HRM? From the perspective of middle-level managers, who should be responsible for decision-making—AI or people? What criteria should organizations use to assess employee performance? How do managers evaluate the fairness of AI-HRM, and what are their views on its trustworthiness and explainability? Finally, who should bear responsibility for AI-HRM? To address these questions, this study conducted 21 semi-structured interviews, including two open-ended questionnaire interviews, to gather qualitative data. The analysis of this data was performed using word frequency, word sentiment, and thematic analysis.

This study contributes to the ongoing research on AI-HRM by addressing the ethical and legal challenges highlighted in the research agenda of Budhwar et al. (2022). By focusing on middle-level managers from high-tech companies, this study aims to investigate their ethical concerns, as these managers are crucial in creating an environment conducive to the future acceptance of AI-HRM. Such an environment is expected to enhance performance at individual, group, and organizational levels (Budhwar et al., 2022). Additionally, this study supports the strategic implementation of AI-HRM, recognizing that middle-level managers play pivotal roles in facilitating strategic AI transformations within organizations (Connelly et al., 2021).

2 Literature Review

2.1 Artificial Intelligence Leverages Human Resource Management Performance

The infusion of algorithms has significantly transformed the HRM landscape, particularly because HRM has traditionally been one of the least data-driven business functions (Cheng & Hackett, 2021; Davenport, 2014). The incorporation of AI and machine learning enables organizations to analyze HRM practices, employee behaviors, and outcomes across various HR sectors. These sectors include HR planning, recruitment and selection, training and development, performance management, reward management, career development, and industrial relations (Cheng & Hackett, 2021; Peng, 2023).

Algorithms play a heuristic role in developing HRM theory and expanding HRM practice. In practical terms, algorithms and human interventions are inseparable; while algorithms provide valuable insights and assist in decision-making, human involvement remains indispensable. This collaborative approach, known as augmentation, underscores AI's role in supporting humans in making final decisions (Hofeditz, Clausen, et al., 2022).

The integration of algorithms into HRM offers organizations the opportunity to enhance overall HR-related performance and unlock their potential (Tambe et al., 2019). By automating routine HR processes, algorithms allow HR practitioners to shift their focus from mundane tasks to strategic management activities that are directly related to organizational development. This shift enables HR professionals to devote more time and energy to higher-level strategic initiatives, thereby increasing their contributions to organizational growth and success (Upadhyay & Khandelwal, 2018). Previous investigations have explored both individual and organizational outcomes associated with integrating AI into the workplace (Budhwar et al., 2022). On an individual level, positive outcomes include job satisfaction, performance enhancement, knowledge sharing, and commitment, while negative outcomes encompass occupational shock, turnover intention, job insecurity, perceived stress, and identity struggles. At the organizational level, positive outcomes include customer satisfaction, HR cost efficiency, increased productivity, and improved service quality. In contrast, negative outcomes may involve actual turnover, negative goodwill, and adverse financial repercussions (Budhwar et al., 2022).

As AI advances, organizations increasingly view algorithms as viable tools in recruitment. These AI applications range from tracking and analyzing recruitment efforts (Kumar, 2012) to reducing discrimination during hiring processes (Newman et al., 2020; Rathi, 2018; Upadhyay & Khandelwal, 2018). In the recruitment and selection process, algorithms contribute to various tasks, including vacancy prediction, job description optimization, targeted job advertising, multi-database candidate sourcing, CV screening, AI-powered psychometric testing, video screening, employer branding monitoring, chatbot services, automated scheduling, and background checks (Albert, 2019).

Furthermore, in other HRM functions and areas of organizational management, such as employee relations, training and development, performance and reward management, strategic alignment, and organizational governance, AI technology service providers play a significant role to provide programs and tools to optimizing organization operation efficiency (Budhwar et al., 2022; Radonjić et al., 2022). Overall, it is generally believed that AI-powered system is helpful tool for HRM.

2.2 Artificial Intelligence Ethic Theory in Human Resource Management

Despite the numerous advantages and benefits introduced by Artificial Intelligence, ethical challenges are of paramount importance in ensuring the development of robust and morally sound AI systems that guide human activities in the right direction. Previous studies have explored the ethical dimensions of AI

(Barredo Arrieta et al., 2020; Castelvecchi, 2016; Garcıa & Fernández, 2015; Huang et al., 2022; Jobin et al., 2019; Mehrabi et al., 2021; Mothukuri et al., 2021; Ryan & Stahl, 2020; Siau & Wang, 2020; Y. Zhang et al., 2021). These AI ethical issues encompass risks associated with AI, guidelines and principles governing AI ethics, approaches to addressing ethical concerns in AI, AI ethics evaluation, and prospective ethical challenges in AI (Huang et al., 2022).

The construct of AI ethics is a central focus, encompassing both the ethics of AI and ethical AI. The former involves ethical theories, guidelines, rules, principles, and regulations, while the latter emphasizes AI's ability to uphold ethical values and exhibit ethical behaviors (Siau & Wang, 2020). Significant attention has been directed toward AI ethical issues, including transparency, explainability, data biases, data security, privacy, and other ethical challenges introduced by AI-based technologies (Siau & Wang, 2020). Ethical issues in AI management can be categorized into three groups. The first pertains to features of AI, such as transparency, data security and privacy, autonomy, intentionality, and responsibility, which give rise to ethical dilemmas. The second category involves human factors contributing to ethical challenges, including accountability for AI-made decisions, the formulation of ethical standards for AI-powered technologies, and adherence to human rights laws by AI-based software. The third category of AI ethics concerns its societal impact, addressing issues such as automation and job displacement, AI accessibility, democracy, and civil rights (Siau & Wang, 2020). These categories advocate for the development of ethical AI systems designed to recognize and appropriately address these ethical issues.

Huang et al. (2022) further categorize AI ethical issues into individual, societal, and environmental levels, arguing that this classification is comprehensive and encompasses the themes discussed in other studies. At the individual level, ethical concerns related to AI empowerment include safety, privacy, and data protection. Societal-level considerations involve ensuring fairness and justice, as well as addressing issues of responsibility and accountability. Lastly, ethical issues at the environmental level pertain to natural resources, sustainability, and other environmental impacts. This multi-level categorization offers a holistic perspective on the ethical dimensions of AI, facilitating a thorough understanding of the complex ethical landscape surrounding AI technology.

Yu et al. (2023) reviewed articles from key journals and concluded that AI adoption and application can be divided into four subsystems: the personnel system, the technical subsystem, the organizational structure subsystem, and the environmental system. They found that, from the perspective of the personnel subsystem, AI adoption within organizations is influenced by demographic characteristics, psychosocial aspects, and professionalism. They propose that the personnel subsystem, particularly in relation to social and people-related factors, plays a crucial role in AI adoption and application in the workplace. These factors are closely related to ethical issues.

2.3 Ethical Challenges within AI-HRM Design and Implementation

Recruitment bias poses significant threats to organizational development. An unjust recruitment process that discriminates against diversity not only undermines organizational growth but also stifles creativity within the workforce (Swartz et al., 2019). In response to these challenges and the call for increased diversity (Ajunwa, 2019), organizations have reviewed their current hiring processes and identified inherent biases against protected groups, such as pregnancy and maternity, as defined by the "Equality Act 2010" (2010). Implicit biases, such as geographical preferences and educational background, have also been recognized, hindering the accurate selection of qualified candidates. To address these issues, HR managers are considering the implementation of AI-powered systems to substantially reduce bias in the hiring process. However, tackling these ethical issues within the management process remains challenging, as significant obstacles persist.

Previous research underscores the importance of employees possessing knowledge of AI management, particularly in areas like data collection and the ability to verify information generated by systems (Budhwar et al., 2022; Tambe et al., 2019). This is critical because data collection and decision-making systems based on algorithms profoundly impact employees' attitudes and behaviors (Connelly et al., 2021). Consequently, data collection and usage have become focal points for organizational AI governance. Ethical concerns have been raised in companies from South-East Asian countries regarding increased surveillance and intrusive monitoring (Kshetri, 2021). These privacy issues are closely related to the data collection process, as algorithms heavily depend on such data. Incessant tracking systems may infringe on employees' privacy rights (Huang et al., 2022). For instance, in China, some firms use applications to continuously track employees' behavior, leading to counterproductive reactions (Huangshi et al., 2022). In this context, organizations should exercise caution when collecting and analyzing employee data to avoid legal risks. Maintaining open and transparent communication with employees is imperative to ensure the effective, secure, and reliable functioning of AI systems. Therefore, organizations should engage in dialogue with employees about data collection and the application of AI (Berente et al., 2021; Budhwar et al., 2022).

The literature also highlights the presence of racist and sexist biases in certain AI applications (Tambe et al., 2019). Addressing these biases is crucial to ensure that AI systems are designed and implemented in a way that upholds fairness, equality, and non-discrimination. Some studies suggest that AI-enabled decision-making processes can perpetuate these biases (Ajunwa, 2019; Li et al., 2021; Raghavan et al., 2020). AI systems may mirror unconscious biases present in the training data, which may not fully represent the entire population (Yarger et al., 2020). The use of biased data in AI systems can reinforce existing biases in the recruitment process (John-Mathews et al., 2022; Tambe et al., 2019). Moreover, biases in training data can result from the overrepresentation or underrepresentation of certain social groups, leading to imbalanced decision models (John-Mathews et al., 2022). Consequently, decisions may diverge from the principles of equality and diversity in recruitment due to inadequate incorporation of data patterns and frequencies (Tambe et al., 2019). Research from the University of Cambridge further questions the feasibility and effectiveness of AI-based solutions in addressing bias and discrimination, emphasizing the limitations of impersonal learning processes (Hocken, 2023).

Previous academic research has identified several factors that contribute to the biased nature of automated recruitment processes (Ajunwa, 2019). First, features of automated hiring platforms may covertly exclude applicants from protected categories without leaving any evidence or record. Second, these systems may use proxies, such as gender or race, which can present discriminatory employment outcomes as fair and unbiased. Third, intellectual property laws, particularly trade secret protections, shield automated hiring systems from external scrutiny, allowing discrimination to go unnoticed. Finally, the lack of control that workers have over the portability of applicant data collected by automated hiring systems increases the likelihood of recurring employment discrimination, resembling a form of "algorithmic blackballing" (Ajunwa, 2019). These factors collectively contribute to the perpetuation of biases and discrimination within automated recruitment processes. Additionally, established organizational hiring cultures, such as value congruence-based recruitment, pose threats to recruiting equality within an organization, as they may favor homogenous job seekers over individuals from diverse background (Ajunwa, 2019). Another challenge posed by AI-involved hiring processes is that job seekers may be reluctant to challenge decisions due to the complexity of the algorithms. This underscores the importance of addressing these ethical considerations in the development and implementation of AI systems in HRM to ensure fair, transparent, and unbiased practices (Budhwar et al., 2022; Tambe et al., 2019).

The fairness of an organization is another ethical challenge when AI is adopted in Human Resource Management (HRM). Prior studies advocate for the integration of AI-based systems to address fairness issues (Hofeditz, Clausen, et al., 2022; Hofeditz, Harbring, et al., 2022; Hofeditz, Mirbabaie, et al., 2022; Sühr et al., 2020). Organizations have shown interest in employing AI-powered systems for applicant preselection, aiming to mitigate biases during recruitment, as AI is perceived as a more objective and less biased system compared to human decision-makers (Black & van Esch, 2020). Management studies argue that predictive AI systems can significantly assist organizations in tracking and managing employee efficiency. By leveraging the increased speed of data storage and the processing power of AI, organizations can facilitate more insightful and effective decision-making in HR processes, ultimately improving overall performance and productivity (Radonjić et al., 2022).

However, anecdotal studies suggest that algorithm-based decisions in HRM are often perceived as less fair compared to decisions involving more human input (Newman et al., 2020). While algorithmic decision-making has the potential to improve procedural justice by eliminating biases associated with human judgment, people often subjectively perceive these algorithms as violating procedural justice. This perception arises because AI tends to focus on easily quantifiable performance data and may fail to consider past performance and other qualitative factors (Hofeditz, Harbring, et al., 2022).

More ethical critiques and challenges exist when applying AI decision making in HRM (Rodgers et al., 2023). or example, the effectiveness and validity of algorithms can be significantly influenced by job contexts and the information provided by candidates (Black & van Esch, 2020). Job applicants might even falsify their CVs to align with the preferences of algorithms. Other concerns include biased decision-making systems, opaque algorithms, and invasive tracking systems that compromise workplace privacy (Ajunwa, 2019; Li et al., 2021; Raghavan et al., 2020). Managerial transparency could be obstructed because of Blackbox in algorithms (Castelvecchi, 2016) which leads to distrust among employees (Naseer et al., 2021). Additionally, research suggests that employees may experience distrust, stress, and other negative psychological responses when interacting with AI systems (Naseer et al., 2021; Yu et al., 2023). This can even lead to counterproductive behaviors, such as service sabotage (Ma & Ye, 2022). These factors contribute to the inadequate reception of AI-HRM systems within organizations (Yu et al., 2023). Overall, while AI-HRM implementations have received praise, ethical considerations and critiques persist. These concerns underscore the need for careful consideration and ongoing monitoring when implementing AI software in HRM to ensure fair, transparent, explainable, and unbiased practices (Barredo Arrieta et al., 2020).

3 Methodology

The present study aims to investigate middle-level managers' responses to AI-HRM ethical issues. Existing studies have utilized qualitative research methods, such as open-ended interviews, to collect qualitative data (Laurim et al., 2021; Li et al., 2021; Ochmann & Laumer, 2019). In alignment with these research designs, this study employs specific groups to gather qualitative data through semi-structured interviews. The interview questions are designed based on previous studies (Laurim et al., 2021; Li et al., 2021; Ochmann & Laumer, 2019), while also taking the contextual background into account.

3.1 Case Selection and Sample Collection Criteria

This study chose Beijing, the capital city of China, as the research site and has targeted middle-level managers from high-technology firms. Renowned for its status as a prominent locus of innovation and scientific advancement in China, Beijing earned the distinction of ranking third in the Global Innovation Hubs Index (GIHI) 2023 Overall ranking (Global Innovation Hubs, 2023). As a leading site of China's burgeoning innovation landscape, Beijing proffered an ideal place to recruit sufficient samples regarding this research topic.

To ensure the quality of data, stringent selection criteria were applied for participant inclusion. Foremost among these criteria was the requirement for individuals to possess a nuanced understanding of the research topic. Consequently, prospective participants were expected to demonstrate proficiency in the domain of AI-infused management within the context of HRM. Additionally, preference was given to candidates affiliated with high-technology firms or those closely associated with such entities. The scale of firms, particularly measured by the number of employees, was recognized as a pivotal factor in assessing technology adoption within organizational management contexts. Therefore, this study primarily targeted large-scale entities, acknowledging their propensity for more extensive and sophisticated utilization of modern technologies. By focusing on such firms, the study aimed to glean insights into the nuanced dynamics of technology integration within expansive organizational frameworks, thereby enhancing the comprehensiveness and applicability of the findings. Moreover, participants were ideally positioned within the organizational hierarchy as middle-level managers or HR managers, ensuring they possessed the requisite depth of insight into HR-related matters.

3.2 Interview Design

A semi-structured interview approach was employed in this study. The interview questions were designed based on the research questions and by referring to previous studies (Laurim et al., 2021; Li et al., 2021; Ochmann & Laumer, 2019). Interviewees were asked open-ended questions, such as "What are your general feelings toward AI-HRM?" These questions were crafted to correspond directly with the research objectives of the study.

Two principal methods were utilized for administering the interviews, depending on participant availability. The first method involved remote interviews conducted via WeChat Voice Call, while the second method entailed the distribution of open-ended questionnaires. The success of using WeChat Voice Call for collecting qualitative data was evidenced by the friendly and interactive relationship established between the interviewer and the interviewees. To further encourage participation, each participant was given 30 Chinese Yuan as Lucky Money through WeChat, which helped increase their interest in participating. The interview process was divided into several stages. First, the interviewer welcomed the participants. Second, respondents provided personal information, including demographic details such as age, education, job title, and organizational details like employer size and industry sector. Third, participants answered the interview questions. Finally, the interviewer closed and concluded the interview.

3.3 Recruitment and Interview Process

Depending on the network of the authorial team, a snowball technique was employed to solicit samples, whereby interviewees were requested to nominate individuals within their social circles possessing substantial expertise in HR management for thematic discussions. Subsequently, authors established virtual connections with these managers to conduct interviews. Consistent with extant literature (Bhave et al., 2020; Suen et al., 2019), inquiries about the ethical propriety of data collection and processing by employers emerged prominently during discussions. All participants were formally apprised of the confidential nature of the interviews, ensuring anonymity and strict confidentiality of both their personal information and the discourse content. It is imperative to emphasize that the present study was exclusively conducted for scientific research purposes, because some participants assumed that interviewer team is from AI-application company.

3.4 Data Analysis

Transcripts were systematically gathered, compiled, and clarified. Within this procedural framework, CapCut was employed as a useful tool for automating the conversion of auditory inputs into Chinese characters, although it was prone to occasional inaccuracies. Ensuring the accuracy of transcripts was imperative, necessitating meticulous manual review to eliminate errors, a process thoroughly overseen by the author team.

After data collection, transcripts were converted into Word documents. This study utilized a word frequency mapping approach to delineate the overall data landscape, facilitated by NVivo 12 Plus. NVivo 12 Plus is a powerful text mining tool that provides robust support for word frequency analysis. During data processing, specific filtering rules were adopted, including setting a minimum word length of two Chinese characters, listing the top 1,000 most frequent words, and applying word generalization grouping (e.g., “communicate”). Words that appeared less than three times were excluded from the analysis. An iterative process was then used to manually exclude redundant and unimportant words, such as “one, ” “one piece,” “somewhat,” and “what.” Additionally, repeated phrases from both the interviewer’s and interviewees’ speech were removed. For instance, if interviewees reiterated their opinions, the duplicate phrases were automatically excluded.

Following this, Python programming, in conjunction with SnowNLP, was employed for word sentiment analysis, enabling the discernment of participants’ affective responses to inquiries, despite some inherent limitations. SnowNLP has been extensively used for analyzing Chinese texts, particularly in online text data analysis, and in line with Wang et al. (2022), this study assumes it to be a robust research tool for data analysis. Finally, leveraging the textual data, the study conducted a thematic classification followed by discourse analysis, in accordance with the method outlined by Braun and Clarke (2019).

3.5 Reliability and Validity

Table 1 Reliability and Validity of the Present Study

Reliability and Validity	Procedures	Action	Check
Reliability	Building a qualitative database of over 17000 words using interviews	Data Management	√
	Design questions based on research questions and purpose	Interview	√
Content Validity	Multiple sources from various hi-tech companies and industries; sample selection criteria	Sample Selection	√
Internal Validity	Data saturation judgment based on theme occurrence	Data Analyses	√
	Discussing themes with professionals, professors	Data Analyses	√

External Validity	Compared results with existing literature and themes, alignment and contrasting	Data Analyses	√
	Check word frequency using the Word Search Function to ensure no new theme occurrence.	Data Analyses	√

Table 1 shows the reliability and validity of this study. The author team considered various factors affecting the research reliability and validity and utilized a series of procedures to check the whole research process. In different stages, the author team has ensured reliability and validity of data and data process.

4 Findings and Analysis

4.1 Participants and Themes Summary

Table 2 illustrates the demographic details of respondents. This study determined the number of 21 respondents because interviewees generated sufficient data, and this study did not find new themes in the transcripts. Therefore, this study supposed that data saturation is reached based on guidance from Braun and Clarke (2019). Among respondents, all have at least a college degree, while 8 of the 21 interviewees are female managers. Nearly half of them (10 of 21) are in their 30s, and 8 participants are in their 40s. Only three participants are in their 20s. The employers' size varies from 500 to 500000 in terms of employees' number.

This study employed two major ways to conduct interviews depending on the availability of participants. The first method is a remote interview via WeChat Voice Call, and the second is an open-ended constructed questionnaire. Most participants accepted our online interviews (19 of 21), and their responses were insightful for this study compared with those from paper interviews. The duration of voice calls ranged from 10 to 45 minutes, depending on the knowledge of the participants, and on average, the voice calls lasted for 28.89 minutes. For 21 interviews, this study collected 170000 Chinese characters, including responses from two open-ended questionnaires.

Table 2 Respondents Information Summary

R.	Industry	ES	Job Position	G	A	EA
1	Technology Media	1000+	Operation Manager	M	30+	U
2	Finance Technology	1000+	Investment Manager	M	30+	P
3	Top Technology Company	30000+	Business Manager	M	30+	P
4	A Medium SaaS Firm	100-500	Sales Manager	M	30+	U
5	Pharmacy Technology Service	1000+	Sales Engineer	M	40+	U
6	Smart Engineering	500-1000	Sales Manager	M	40+	U
7	Top Tech Recruitment Agency	10000+	Government Relation Manager	M	40+	P
8	Top Search Engine in China	35000+	Programming Leader	M	30+	P
9	Heat Engineering Company	100-500	Vice General Manager	M	40+	P
10	Top Consulting Company	1000+	Leader of AI-HRM project	F	40+	P
11	Top Dentist Hospital	1000+	Former Director of HR Department	F	40+	U
12	Top Technology Company	30000+	Former HRBP & HR Specialist	F	30+	P
13	Second-tier Technology Company	1000+	Recruiter Specialist HR	F	25+	P

R.	Industry	ES	Job Position	G	A	EA
14	Second-tier Technology Company	1000+	Manager of Remuneration and Performance	F	30+	U
15	World Top 500 Company	100000+	Sales Manager	M	40+	U
16	Top Technology Company	500000+	Procurement & Sales Manager	M	20+	U
17	State-owned Conglomerate	16000+	HR Director	M	40+	P
18	Technology Finance & Insurance Corporation	2000+	HR Specialist	F	30+	P
19	Automobile Tech Factory	1000+	HR SSC, HRBP	M	25+	U
20	Technology Company	1000+	Sales	F	30+	C
21	Industry Internet	1000+	HR Manager	F	35+	U

Note. R is short for respondent serial number; ES is short for Employee Scale; G is short for Gender; A is short for Age; EA is short for Education Attainment; U is short for Undergraduate Level; P is short for Postgraduate Level; C is short for College Level.

Figure 1 shows general attitudes and the themes of this study. This study categorized three bundles of emotion patterns toward AI-HRM and concluded that “questioning”, “reflection”, “recommendation”, “challenging”, “adaption”, “resistance”, “unawareness”, and “indifference” are respondents’ emotions based on excerpts. Existing emotions, including “questioning”, “challenging”, and “resistance,” reflect some respondents’ incredibility and negativity toward AI-HRM. For instance, R4 argued that *“HRM is too complex to use AI because AI is too stupid to* cope *with e*thical issues.” “Reflection” indicates that some managers reflect on their tasks using modern technology. “Recommendation” and “adaption” indicate positive emotions toward AI-HRM, which shows managers are embracing new technology. The “indifference”, “unawareness”, and “unknown” emotions are commonly exhibited among respondents, especially when they are not really related to managing HR affairs or are familiar with HR business or AI-HRM. For instance, “I do not care about these things. I care about results. R6.”

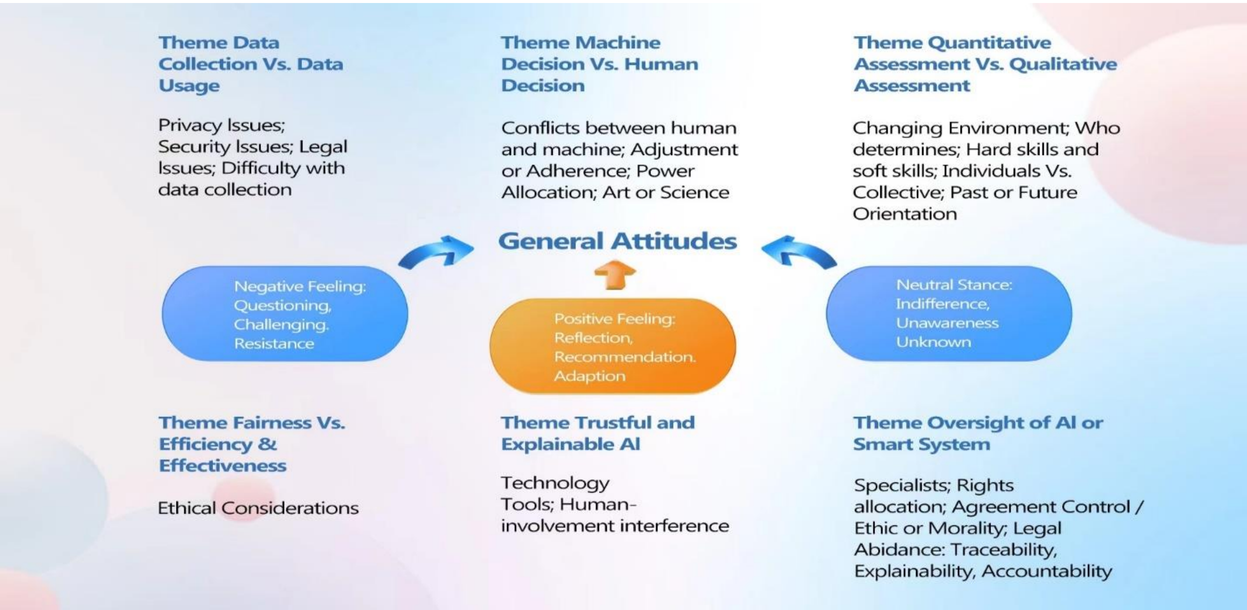

Figure 1 Ethical considerations around AI-empowered HRM

Figure 2 delineates the lexical theme derived from respondents' input, meticulously crafted using Nvivo12 Plus. The process of constructing this visual representation is presented as follows. First is a detailed curation of word frequencies according to specific parameters. These rules included a minimum word length of two Chinese characters, listing the top 1000 most frequent words, and applying word generalization grouping (e.g., "communicate"). The frequency of words appearing less than 3 times was removed. An iterative process was used to manually exclude redundant and unimportant words, such as "one," "one piece," "somewhat," and "what." Additionally, similar words from the interviewer's speech and repeated expressions from interviewees were removed. This careful process resulted in a list of meaningful word frequencies, as shown in Table 3.

4.2 Word Frequency Analysis

Figure 2 Word Cloud of Transcripts

According to Figure 2, a notable change occurred because "Change" was marked as the most frequently appearing word in the transcripts. This change is because similar words to "change," such as "revise," "revision," "amend," and "vary," have been counted toward the frequency of "change," but this revision has not been reflected in the word cloud image generated by NVivo 12.

Word	Change	Company	Data	System	Needs	Problem	Cause	Move	Employee	Thought
Frequency	1404	1393	1246	1181	1131	1093	959	824	739	722
Ranking	1	2	3	4	5	6	7	8	9	10

Word	Compare	Concept	Track	Monitor	Distribution	Confidential	Assess	Firm	Collect	Determine
Frequency	632	582	567	439	416	394	384	372	350	286
Ranking	11	14	15	19	20	23	24	26	30	38
Word	Plan	Resource	Design	Recruit	Evaluate	Fair	Training	Solution	Appraise	Anyway
Frequency	258	258	226	218	199	182	177	167	145	131
Ranking	40	41	51	53	60	68	71	75	89	95

Table 3 Words and Equivalence Frequency among Interviews

Note: Words or equivalent words used in "generation grouping" via Nvivo12 Plus

Table 3 shows that the word "change" is the most common occurrence among interviewees when they reflect on the questions about AI or related technology used in the workplace. Subsequently, "company," "data", "system", and "needs" are the top 5 words that frequently appeared in discussions, which shows key issues that respondents are concerned about. Other word frequencies followed together to form the illustration of the word cloud. Please see Figure 1.

4.3 Sentiment Analysis of Transcripts

Using NVivo 12 Plus, this study generated 1000 frequent words, and then this study analyzed the sentiment of these words using the Python SnowNLP process. This study inputs 1000 words into the Python training model and calculates the sentiment scores of words. As shown in Table 4, the words that most frequently appear are neutral, while positive and neutral words together account for approximately 90% of the total 1000 frequently appeared words. This suggests that respondents are generally positive and neutral toward AI-HRM.

Table 4 Words Sentiment and Frequency

Emotion Assessment	**Positive**	**Neutral**	**Negative**
Frequency	226	673	101
Sentiment Score	>=0.7	(0.3-0.7)	<=0.3
Percent Account	22.6	67.3	10.1

Figure 3 shows the Bubble Chart of Selected Words Frequency used in Table 2. The X-axis shows the sentiment of words, the Y-axis shows the general category of emotions, whereas the size of the bubble shows the frequency of words. To draw this figure, this study first included the most frequently appeared 100 words based on analyses of transcripts. Then, this study selected the 12 words with the highest frequency along with other words. Taken together, this study selected 30 frequent words from transcripts to demonstrate the sentiment trend of words. A close examination can be seen in Figure 3. The X-axis ranges from 0-1, which indicates the sentiment score of words. The Y-axis has been divided into three levels of feelings, namely 1, 2, and 3, which respectively show negative, neutral, and positive. This category is in line with previous word sentiment analysis from Wang et al. (2022). According to Figure 2, it is noted that the negative words counted less proportion of overall sentiment distribution, and the most frequently appeared words (the bubble size) are either neutral or positive. Therefore, Figure 2 and Figure 3 are consistently reflective of this trend.

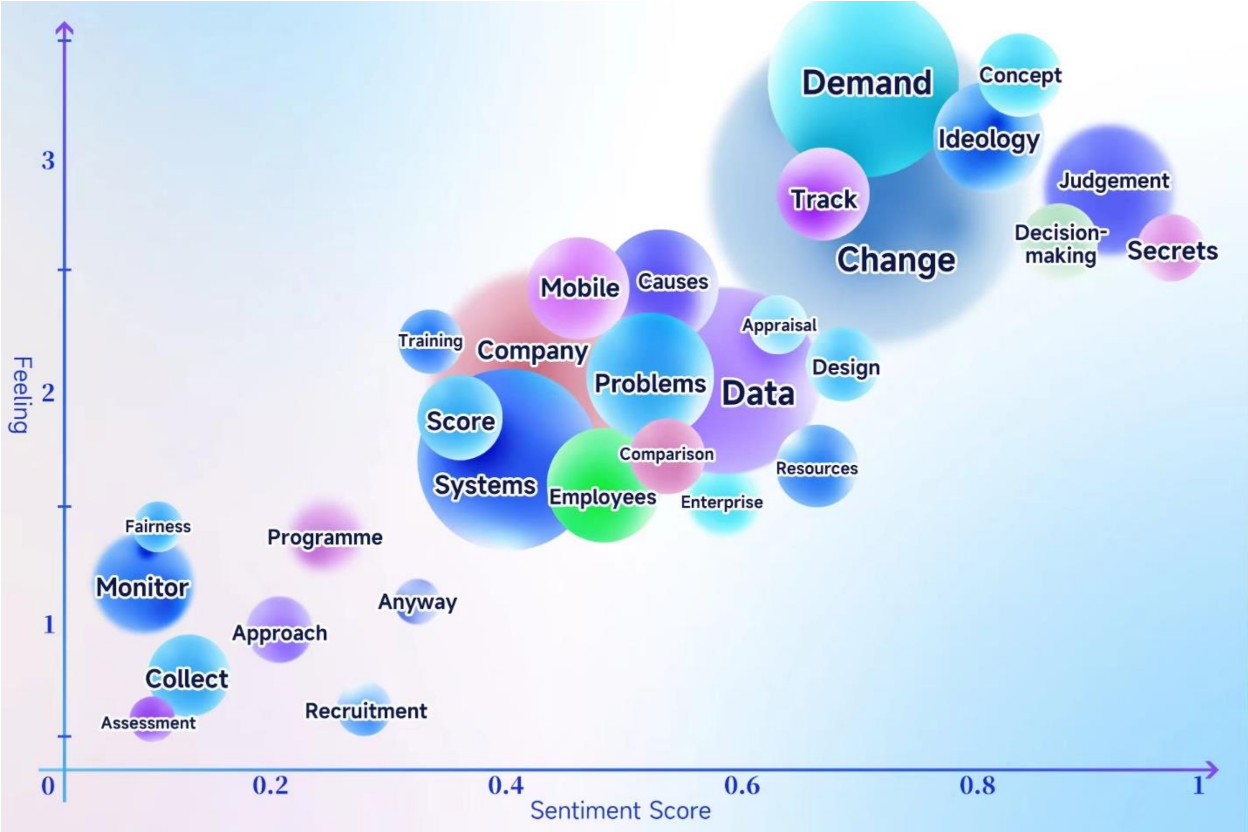

Figure 3 The Bubble Chart of Selected Words Frequency

4.4 Theme Data Collection Vs. Data Usage

The issue of data collection is crucial in discussions about employees' privacy rights within organizations (Y. C. Zhang et al., 2021). However, the study reveals that many respondents believe it is legitimate for organizations to collect their data and information at work. This finding is explained through four main areas related to data collection: privacy intrusion, security and safety concerns, the complex mix of legal and illegal issues, and the challenges associated with gathering data. The most significant question raised is whether employees' behaviors within the workplace should be considered privacy. An overwhelming majority of respondents (17 out of 21) unanimously agree that the implications are critically dependent on how organizations utilize the data. One respondent stated, *"As HRs, we will not use your data to check your daily behavior unless you have conflicts with organization management. In fact, the surveillance or other facilities will generate a large volume of unstructured data, so it is barely possible to track every employee on a daily basis."* Additionally, several respondents argued that once employees sign a labor contract with the employer, they agree to provide their information and allow the monitoring of their behaviors in the workplace (R1, R2, R5, R14, R15, R17, R18). Another respondent highlighted the complexity: *"It is difficult to say no in the workplace. For instance, if surveillance cameras in the office are installed, these instruments will track employees' behavior now and then for security or safety reasons. However, these data will be a grey area in terms of privacy because it is hard to discern privacy from* *work behaviors"* (R11). R17 strongly argues that *"There is no point in discussing privacy in the workplace. For instance, if you reject the management agreement, you will not receive a job offer. In this sense, you need to surrender your privacy in the workplace. It's similar to the situation with apps on your mobile phone—if you decline the privacy agreement, you cannot download or use the apps. Indeed, our lives in modern society are transparent."* R2 adds, *"Some employees will still have objections, huh? Yeah, they will have some too. However, they do not dare to speak out. Some of them do, but it's usually just a tirade. (R2)."*

Second, data collection and usage are closely tied to security and safety concerns in the workplace. For certain positions, such as key programmers or top executives, their computers and other devices are closely monitored to prevent data leakage. Other data collection methods, such as camera surveillance and application tracking, are employed to mitigate safety risks, such as theft or sabotage. As R16 explains, *"Data security is the top priority in our organization since we have millions of consumers' information. Therefore, we classified information security levels for different positions. So, if you are one of the top executives or engineers who have access to the key database, you will be subject to stringent surveillance. However, for general employees, they are not strictly managed and monitored. (R16)."*

Third, participants generally agree that protecting employees' privacy in the workplace is challenging. There is debate among respondents about whether collecting personal data in the workplace is legal, illegal, or falls into a grey area. R17 highlights this ambiguity, stating, "*The data collected by the organization is not accessible to general employees. Therefore, when employees attempt to file lawsuits against the employer, they do not have access to their data from surveillance instruments. (R17)."* This perspective reflects a common understanding of data collection practices in the workplace and data collection and storage is the property of orgnization. R12 offers further insight: *"It is legal if we do not intentionally misuse or leak the data. For instance, if employees terminate their labor contract with the organization, their data will be completely deleted after a period, usually 2 or 3 years. We do not store it for other purposes. However, if you violate organizational laws or regulations, or engage in illegal behaviors such as theft, workplace harassment, or office fights, we can review videos to validate the actions."*

HR professionals also acknowledge the challenges in tracking employees, even when the company mandates the installation of software on employees' mobile phones. R18 observes, *"Employees can play tricks. We asked them to install organization-developed apps, and they did so with one phone. However, they have another phone for daily use. This way, they can avoid providing any private information to the organization because we cannot track their private phone."*

Fourth, the data collection process can be challenging as it requires significant employee effort and involvement. R6 argues, *"We are exhausted from filling out various forms of data, but there isn't a smart way to collect data for the smart systems. Different applications have different requirements, and sometimes, we need to do repetitive work to fill out the forms or provide data. It is neither smart nor efficient."* This sentiment highlights the inefficiencies in current data collection methods. Regarding HRM tasks, a substantial portion of job responsibilities relies on human involvement. For instance, general employees must manually provide their sales or other quantitative data to their managers.

4.5 Theme Human Decision Vs. Machine Decision

The advent of artificial intelligence (AI) has introduced advanced technological capabilities that enhance managerial functions. Nevertheless, it inevitably raises discussions on organizational ownership and governance (Lindebaum et al., 2020). Achieving a high level of AI within Human Resource Management

(HRM) is still challenging, mainly due to the lack of comprehensive details in all areas relevant to AI-HRM, which hinders precise decision-making processes. In this context, the contrast between human and automated decision-making is a topic. Various extracts and sub-theme evidence support this overarching theme, including conflicts between human and machine decisions, adjustments or adherence within organizational management, power allocation and organization control, and the debate between viewing management as an art or a science.

Conflicts between human decision and machine decision

Respondents exhibit a robust consensus advocating for human involvement in decision-making over machine decision-making. At present, notwithstanding the sophistication of intelligent applications or AI-driven human resource management (AI-HRM) platforms, they remain incapable of consistently rendering accurate decisions. For instance, R12 argues that *"quantitative data is a part of the decision-making process, but when you manage human resources, what you cannot avoid is the involvement or intervention from leaders, managers, and other high-ranking officials."* Additionally, R12 notes, *"whether a leader wants to promote a subordinate is not only based on quantified performance but also on other considerations, such as opportunity, fit, and networks."* Conflicts persist between human judgment and automated processes, precluding unequivocal reliance on AI or machine-generated decisions. This aligns with previous studies, which underscore the need for integration between human decisions and machine decisions (Hofeditz, Clausen, et al., 2022).

Adjustment or Adherence

Aligned with section 4.3.1, apprising employees may involve both machines and human beings working together. For example, if an employee receives a B in their performance appraisal from a machine-based evaluation, their leader may adjust the assessment by considering other contributions or negative behaviors. In this dynamic, human intervention becomes an integral part of the decision-making system. Consequently, the process of "making adjustments" and "adhering to" machine-generated decisions becomes intricate and multifaceted. R14 remarked, *"you cannot fully adopt decisions made by algorithms because management decisions involve various considerations. They should be directed by people, which means there is an element of fairness or personal judgment because numbers are cold and faceless. Since the goal of performance management is to manage people, it has to be comprehensive and involve compromises in the process of organizational management."*

Power Allocation and Organization Control

The investigations reveal a prevalent reluctance among managers to embrace automated decisions in HRM. Most managers express skepticism about the ability of AI to make decisions, arguing that it cannot replace human involvement in decision-making processes. On the one hand, current AI-HRM systems have inherent limitations in effectively handling complex scenarios. As R17 stated, *"it is still too simple to manage various networks and relationships. For instance, who are the close allies of executives? Deciding these people should be done very carefully."*

On the other hand, power is very important to managers because it allows them to exert control and direction over subordinates. The high frequency of keywords like "track" and "monitor," reflecting the desire for power allocation, frequently appears in the transcripts (please see Table 3). For instance, R12 stated, *"This is all controlled by humans. The system gives you a suggestion. In fact, you must adjust these things with your will. To put it bluntly, it is the boss who has the final say in this company, not the system."*

Art or Science

Algorithms are based on historical data and are highly rational because they are designed for optimization, operating through logical and mathematical procedures (Lindebaum et al., 2020). However, the nature of management decision-making sparks debates about whether it should be considered an art or a science. Advocates of scientific management argue that sound decision-making requires calculations and analyses, following the principles of classical management theorists such as Frederick Winslow Taylor and Max Weber (Thompson, 2004). In contrast, proponents of a people-centric approach suggest that managers should focus on human considerations. Leaders at the upper levels of management often prioritize performance and make decisions based on subjective judgment rather than solely relying on data and machine-driven decisions. As R1 stated, *"For instance, does AI account for a failure to design and implement strategic management? It is not possible to rely on algorithms to make smart decisions because machines cannot predict the future or know tomorrow's sales performance. Top management needs to make decisions based on information provided by algorithms and their business acumen. Of course, they are the ones who will assume responsibility when their decisions fail to advance the organization."* Additionally, R16 commented, *"managing people is difficult because interpersonal relationships are hard to interpret. Machines cannot track those hidden feelings and agendas among employees because algorithms cannot collect unstructured, changeable data to make predictions. Managing these things is a piece of art that requires a high level of understanding of national culture, organizational culture, and other complicated situations."*

4.6 Theme Quantitative Assessment V.S. Qualitative Assessment

Algorithms heavily depend on data inputs derived from past performance or data collected because AI-HRM systems cannot operate independently of historical data (Rodgers et al., 2023; Tambe et al., 2019). Algorithms are designed within a framework aimed at optimizing decision-making processes (Lindebaum et al., 2020), yet this approach may contradict the notion that organizational performance management should be inherently future-oriented, as advocated by Otley (1999). Upon closer examination of respondents' feedback, certain factors significantly influence performance management, where algorithms fall short in their capacity to match human judgment and intuition. This study finds supporting evidence under this theme, which we categorize as sub-themes.

Changing Environment

Modern management theory posits that contemporary organizational management operates in dynamic interplay with the external environment. Contingency theory asserts that environmental factors function as independent variables, while management policies serve as dependent variables, making organizational management policies difficult to predict due to the rapid and fluctuating nature of the external business environmen (Safari & Saleh, 2020). *"Our strategies are changing so rapidly because, as you know, internet companies are facing an unstable business environment. With the emergence of new business models, technological advancements, and legal regulation changes, our strategic goals are also evolving. Strategic decisions from top management are changing quickly, and structural and implementation changes are being made concurrently. Therefore, all management decisions based on quantitative assessment become outdated when top leaders alter their decisions. (R16)."*

Who determines Performance Assessment?

Evaluating employee performance holds paramount importance for organizational development, raising the pivotal question of who is responsible for performance assessment. Methodologies such as 360-degree feedback, Objectives and Key Results (OKR), or their equivalents, typically involve human intervention in assessing employee performance. Consequently, the implementation of an automated performance and salary management system within an organization remains unfeasible. It is noteworthy that in organizations with a workforce of 10,000 employees or more, the functions of performance evaluation and salary management are typically intertwined rather than segregated, as indicated by R14. *"Last year, when most internet giants decreased their employees' salaries, our boss significantly raised salaries in the sales & procurement department. It is widely known among internet companies in China. So, I think it is impossible to consider AI-involved decision-making because AI will only consider past performance, historical data, and quantitative assessment. (R15)."* In accordance with R17, decision-making by individuals tends to be strategic and qualitative rather than solely quantitative. Should the focus of top management shift from sales to cultivating government relationships, this transition would inevitably alter the landscape of performance management.

Individual or Collective Orientation

A vital metric for performance assessment lies in interpersonal communication skills and the ability to foster meaningful professional relationships, commonly referred to as people networking. *"We have a very good salesperson, and his sales performance is superb, but colleagues and his direct leader are not happy with him because of his arrogance. So, his performance assessment has been under-evaluated. This is because his leader is a collective-like leader, and the work unit should be united to improve overall performance instead of individual performance. (R16)."* Indeed, within an organizational context, effective leadership necessitates a holistic consideration of various interpersonal dynamics such as relationships, collective sentiments, harmony, and morale among coworkers. This assessment approach is indispensable for enhancing overall organizational performance. *"If our sales target in Platform A is 1 million, correspondingly, the organization will put more resources and emphasis, such as marketing expenditure, on Platform A, so there will be a decline in performance in Platform B. You should balance results because it is not the salesperson's fault. It is all about how top executives determine performance orientation. It is a conflicting situation when individual interests collide with collective interests, so AI-HRM is not smart enough to fulfill the organization's strategic needs. (R17)."*

Past or Future Orientation

Historical data form the basis of algorithms. In practice, however, managers do not solely rely on an individual's past performance to determine their future development. For instance, *"our company needs a person who can run a store independently. We will try to promote him/her despite his/her past performance not being so good on paper. Therefore, it is subjective judgment rather than objective assessment. It depends on time, opportunity, and subjective decisions from leaders."* Another example is, *"despite one job candidate seeming perfect on paper—graduated from an elite university, with a good GPA and other qualifications—when our HR people talked to him in person, we found she is more suited for a lecturer or professor position at the university than as an expert in an Internet company because you cannot rely on a person without good communication skills. That is why we focus on future performance and individual traits, not their past performance. (R13)."*

Algorithms undoubtedly offer HR professionals the opportunity to streamline their workflows, saving time and minimizing repetitive tasks by analyzing past performance data. However, they remain an incomplete tool, incapable of entirely replacing human decision-making processes, as they lack the nuanced understanding, intuition, and contextual awareness inherent in human judgment. *"Scoring employees cannot just look at the history; you have to look at the future, you have to consider the employee's potential for development. Whether managers want to train her, including some of the future positioning with him, and so on, this is something AI cannot achieve so far. (R14)."*

Hard Skills or Soft Skills

Assessing employees presents a challenge due to the diverse array of skills they exhibit, each requiring distinct evaluation criteria. Hard skills, such as programming and engineering, lend themselves to assessment through algorithms, leveraging quantitative data for predictive analysis. However, soft skills, which encompass interpersonal abilities and emotional intelligence, defy algorithmic assessment due to their latent, nuanced, and often subtle nature, making them difficult to measure precisely through quantitative means. *"An employee is not qualified based on her performance at the workplace, but her family is influential in a county. If our business encounters difficulties, she will find the right person or relationship to solve the problem. You cannot rely on algorithms to assess her; otherwise, you will lose her ultimately. (R12)."*

4.7 Theme Fairness Vs. Efficiency & Effectiveness

The preceding literature has extensively deliberated on addressing fairness issues through AI-empowered technology (John-Mathews et al., 2022). However, upon scrutinizing organizational management during interviews, it becomes apparent that this is a complex and interconnected issue that is not easily remedied (Ajunwa, 2019). Indeed, AI-HRM lags far behind in resolving fairness-related dilemmas within organizations. For instance, one respondent emphasized the necessity of balancing various interests within the organization, highlighting the challenge of reconciling performance metrics with the well-being of employees. *"We have to balance various interests within the organization. If we completely focus on numbers or performance, we cannot take care of employees. Those elderly employees may no longer be at their prime in terms of their sales performance, but their contributions to the organization at different times are evident. We should take that into account and ensure they are well-treated. This is human intervention when managing various complex businesses. (R6)."* R7 underscored the notion of an organization as a socially bonded entity, cautioning against overreliance on AI in navigating intricate interpersonal relationships. In scenarios such as family-run businesses where familial ties influence decision-making, performance and salary management necessitate flexibility to accommodate stakeholders' interests. *"If an organization is a family business and many family members are in important positions, performance and salary management should be flexible to cater to stakeholders. This is a role that needs HR to understand the big boss' hidden agenda, and it is a complicated and unspoken task when considering fairness within the organization. (R12)."*

Furthermore, a notable gap emerges when considering fairness issues within organizations during discussions among HR professionals. It becomes evident that there is no standardized answer to the question of fairness as respondents question the inquiries posed. One respondent elucidated the organizational priority of survival in the face of external pressures, particularly exacerbated by the aftermath of the Covid-19 pandemic. *"The priority of the organization is to survive. I do not know what you are talking about fairness. As a big organization, especially after the Covid-19 pandemic, we need to cut costs and maintain our business. The external environment is demanding, and the top management of the organization is struggling to sustain our business. You know your topic is not on our table, as we must deal with financial pressures and stay away from bankruptcy. Now, our policies are effective and efficient first. We need to make changes to deal with external economic pressure. (R17)."*

In contrast, some respondents have posited that the utilization of automated decision-making mechanisms, such as machine learning algorithms, may foster fairness in evaluating employee performance, but notable challenges beset the realization of such a high-level AI system. *"I think it is fair. It just depends on how* *fine your (performance) granularity size is. Is the finer, the better? I think it needs the appropriate granularity size, right? Too fine is not good. It is not usable. So, that is hard to control and design. That is the KPI design. Your framework design is what performance indicators you need. What working hours are under the performance indicators support the performance indicators. R10."* In addition, *"line managers are biased. They can neglect your contribution when they find you are useless. I think it is better to use AI-HRM. At least you will not be discriminated against by the machine if the algorithm is set fairly. R3."*

Therefore, the prevailing technological landscape appears inadequate in resolving the intricate challenges surrounding organizational fairness, particularly within the realms of performance and reward management, owing to the multifaceted nature of organizational governance. By contrast, AI-HRM, which is designed with transparent and explainable algorithms, may provide another path for future organizational governance.

4.8 Theme Trustful, Transparent, and Explainable AI-HRM

Trustfulness, transparency, and explainability are key themes of previous studies on AI-HRM (Ajunwa, 2019; Li et al., 2021; Raghavan et al., 2020), but this study found that managers are not significantly concerned with these topics. To build a trustworthy AI-HRM, errors or inconsistencies generated by AI-HRM must be addressed. Currently, there are two primary methods for addressing errors. First, adjustments or fixes can be implemented by the technology department. The interviews indicate that middle-level managers are often unaware of these functions. As one respondent stated, *"I think we have technicians to cope with these technical problems, but I do not know who exactly is responsible for these. (R12)."* Second, individuals involved can enact adjustments. If an employee is dissatisfied with their performance appraisal or salary, they may approach their leaders or superior management for explanation or adjustment, as evidenced by references R6, R7, R9, R10, R11, R12, R13, R14, R15, and R16. Should such issues arise within a department or business sector, the sector leader will typically seek adjustments or changes, necessitating human intervention in the process.

In terms of transparency and explanation, respondents raised a critical question: What is the standard for AI-HRM? R7 pointed out that *"our country or the industry sector does not have a standard for the application of AI artificial intelligence. So, in each company, what kind of software is used, and to what extent is AI applied? In fact, there is no standard. It is a mixture of good and bad. So, it depends on your scenario."* This lack of industry standards leads to the question of how companies can evaluate AI-HRM in terms of transparency and trustworthiness. For example, *"Like some companies, for example, DiDi,"* a Chinese vehicle for hire company, *"is essentially a labor outsourcing company. I think it is a particularly good scenario, as I just mentioned. In fact, AI-HRM is quite suitable for DiDi. It is the so-called employees under its control. It does not matter whether the labor relationship is with the employee or outsourced. It is the administration work content. The way of work is relatively simple and standard."*

Respondent 16 argued, *"I think data is neutral and true. Moreover, I think AI is true if it is designed based on an agreed protocol and transparent rules. However, we should not dismiss the role of management because when the employer selectively collects this data and partly utilizes it to defend themselves, general employees do not have access to the data. That is the key point."*

4.9 Theme AI Oversight

In the workplace, employees often lack awareness of the threats and challenges posed by algorithms and information systems. While they are not expected to have deep technical knowledge, they are interested in understanding the basics that management emphasizes. Human resource managers frequently organize informational sessions to help employees learn about smart applications and intelligent systems. However, these sessions typically focus on procedures and regulations rather than the details of how these systems operate.

The AI-HRM is difficult to monitor as there is no standard to assess these systems R7. *"If we design and implement a system with a group of people and they are top talents of the industry. It is not possible to oversee these people because you cannot find other suitable people to oversee them, and you also need to consider the cost of oversight. Only if big errors occur will you eventually spot problems with AI-HRM. R5."*

Objection to this viewpoint existed. As R8 and R14 pointed out, *"We separate access of AI-HRM. Our internal AI system developers do not have access to the operation system, and managers do not have access to modify the system. If necessary, they need the safety shield to manage the changes witnessed by other people."* In addition, *"if we outsource the system, we will sign the contract with the provider, so there is a regulation document that specifies the details of the system. I believe this is the oversight of AI-HRM. R7."* Or *"our employees develop the system, and they signed an employment contract with us, so they will assume legal responsibility and against risks if they violate rules or conduct harmful behaviors. Besides, they have an ethical responsibility to oversee AI. R15."*

5 Discussion and Conclusion

The findings of this study identified three general categories of emotions toward AI-HRM: positive, negative, and neutral. These categories aligned with sentiment analyses based on a frequency count of 1,000 keywords using the Snow-NLP process. The study categorized "questioning," "challenging," and "resistance" as negative emotions; "reflection," "recommendation," and "adaptation" as positive emotions; and "indifference," "unawareness," and "unknown" as neutral emotions. These categories corresponded to the first research question, which examines the general emotions of middle-level managers in high-tech firms toward AI-HRM. This study assumed that most managers hold a positive view of AI-driven management changes despite previously mentioned ethical concerns. The findings are consistent with the study by Yu et al. (2023), which highlighted that individuals' psychosocial aspects significantly influence AI adoption within organizations, as individual managers make judgments about AI based on their own feelings.

This study undertook a comprehensive investigation of AI-HRM across six dimensions to elucidate diverse managerial perceptions of this emerging field. Ranging from fundamental notions of data collection and utilization to intricate considerations of fairness, efficiency, and efficacy, managers candidly articulated their insights and understanding regarding the advent of AI-HRM. Generally, middle-level managers do not fully support AI-HRM transformation, arguing that it is premature to implement AI-HRM because the HRM system is a complex scenario for adopting AI applications. The results correspond to the second research question of the present study. Trust in AI has determined the acceptance of AI within HRM (Siau & Wang, 2020), and the "black box" nature of AI has perplexed independent reasoning and judgment regarding AI solutions (Castelvecchi, 2016). As Ajunwa (2019) noted, people's decision-making systems rely on reasoning that aligns with an intuitive understanding of a particular question in context, but so far, experts do not consider AI-generated automatic solutions to be reliable today (Berente et al., 2021).

This study investigated different responses to AI-HRM ethical issues to address a range of ethical questions related to AI-HRM implementation. The themes generated from this study echo the propositions defined by Siau and Wang (2020), addressing two categories of ethical AI: features of AI and human-related ethical challenges. AI-HRM encountered difficulties in responding to various external issues. First and foremost, the collection and usage of data emerged as a significant theme in respondents' discussions. Although it is not widely assumed that data collection in the public workplace infringes on employees' privacy, objections are evident. It is debatable whether data collected in the workplace should be considered private, despite the fact that HR managers seldom use this data. As one respondent noted, "employees are blinded toward these data collection and usage in the digital era. R7." In this sense, communication is necessary, as employees' privacy should be protected in case of data leakage (Mothukuri et al., 2021).

Second, regarding human and machine decisions, managers exhibit a favorable disposition toward integrating AI assistance into various decision-making frameworks, instinctively viewing such assistance as a pivotal facet of decision-making. In other words, managerial preference leans toward AI-supported decision-making over a fully automated AI-driven decision-making process, recognizing the inherent complexity and dynamism in human resource management, which necessitates human interventions to navigate these multifaceted and fluid landscapes (Budhwar et al., 2022; Tambe et al., 2019). The implementation of AI-driven decision-making appears distant from practical application due to its potential intrusion upon managerial power. The findings indicate that power dynamics are crucial to managers, who are either actively or passively engaged in the decision-making process, thereby consolidating their influence within the workplace. This argument is also evident in McClelland's motivation theory, which claims that the need to drive other coworkers to behave in a way that they should behave (Cook & Artino, 2016) is an important motivation. The strong desire for power may resist the implementation of automated decisions generated by algorithms. Additionally, this study raised another classic debate concerning whether management science should be regarded as an art or a pure science, because quantified-based algorithms may not consider human beings' intuitive understandings of phenomena in nature (Ajunwa, 2019).

Third, upon further investigation into automated decision-making within the context of AI-HRM, a new theme emerged organically: the dichotomy between quantitative and qualitative assessment in performance management. This theme addresses the question of how organizational management should assess employees' performance. Delving deeper into this subject, it became evident that management practices vary based on several factors, including the external environment (i.e., contingency theory purpose), the flexibility afforded by executives, individual or collective orientations, past or future orientations, and employees' soft and hard skills. These factors play a pivotal role in determining whether employee performance is assessed through quantitative, qualitative, or mixed methodologies. A closer examination reveals a complex scenario wherein organizational management must adapt their strategies or tactics accordingly. This argument aligns with Ajunwa (2019), who calls for thoughtful and meticulous consideration when incorporating AI into organization management.

Fourth, the theme of fairness versus efficiency and effectiveness emerged as this study examined organizational practices involving AI-HRM systems. The findings reveal that while automated decision-making may seemingly offer fairness or objectivity in certain contexts (Li et al., 2021), there are considerable debates regarding what constitutes a balance between fairness, effectiveness, and efficiency (Tambe et al., 2019). Respondents, reflecting on their daily work experiences, agreed that automated decisions are not inherently fair due to various issues, such as system design flaws and the inability to adapt to external or future changes. Organizational management must navigate a landscape characterized by variability, flexibility, complexity, and the need for balanced decisions. This indicates that AI-HRM cannot solve complex ethical problems related to intricate organizational managerial issues (Budhwar et al., 2022).

Fifth, regarding trustworthy, transparent, and explainable AI-HRM systems, respondents predominantly expressed positivity, exhibiting a willingness to overlook concerns regarding AI-HRM applications or the results that they generate, provided there is an agreement in algorithms. By contrast, previous studies argue that communication between management and employees regarding technology design and usage should be open to implement reliable systems (Budhwar et al., 2022). This study posited that employees are results-oriented, and, in fact, they ignore the AI system in use while remaining highly focused on outcomes. Therefore, management should emphasize different aspects when addressing different levels of employees. In instances of perceived inconsistency, respondents demonstrated a readiness to contest decisions, recognizing the potential for employers to exploit stored data and thus paying attention to the power imbalance between the two parties, namely employer and employee. Finally, within organizational structures, oversight of AI-HRM predominantly falls under the purview of the IT department. Managers and general employees are primarily focused on tangible outcomes, such as performance or salary, with little emphasis on AI-HRM governance. Middle-level managers also exhibit a lack of interest in overseeing AI-HRM practices when they are not directly responsible for AI-generated data. These findings are relevant to the research question, "Who is responsible for AI-HRM?"

This study makes major contributions by examining AI-HRM through a unique lens, namely ethical considerations from middle-level managers. It conducted an extensive analysis of 170,000 words extracted from transcripts, examining word frequency and sentiment. These analyses, combined with a thematic categorization of respondents' feedback, facilitated a nuanced understanding middle-level managers from high-tech firms. Consequently, this study identified various themes to distill the essence of the transcripts and gain deeper insights into AI-HRM practices. The empirical findings offers valuable insights for both software developers and organizations engaged in strategic transformations within the AI-HRM, providing diverse perspectives for consideration. Moreover, the theoretical frameworks and themes elucidated in this study pave the way for future research to delve into the ethical dimensions of AI-HRM with a greater clarity and depth.

This study exhibits several limitations. First, due to resource constraints, it was unable to engage high-level managers from first-tier companies, thereby restricting the study's focus to ethical considerations among middle-level managers. Second, respondents were primarily from a Chinese-speaking context, leading to potential disparities between the original Chinese transcripts and their English translation counterparts, despite concerted efforts to mitigate language barriers. In addition, as noted by Yu et al. (2023), demographic characteristics have influenced AI adoption, so it is believed that managers from Western high-tech companies may behave differently responding these interview questions. Thus, the population bias may impair theoretical generalization regarding business management in distinctive cultural contexts. Third, while SnowNLP serves as a handy tool for natural language processing in analyzing sentiment within Chinese texts, its applicability and accuracy are not unequivocal. Therefore, the results or sentiment analyses proffer only a broad overview of textual content.

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References
1. Ajunwa, I. (2019). The paradox of automation as anti-bias intervention. *Cardozo Law Review*, *41*, 1671-1732.
2. Albert, E. T. (2019). AI in talent acquisition: a review of AI-applications used in recruitment and selection. *Strategic HR Review*, *18*(5), 215-221. https://doi.org/10.1108/SHR-04-2019-0024
3. Atack, J., Margo, R. A., & Rhode, P. W. (2019). "Automation" of Manufacturing in the Late Nineteenth Century: The Hand and Machine Labor Study. *Journal of Economic Perspectives*, *33*(2), 51-70. https://doi.org/10.1257/jep.33.2.51
4. Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82-115. https://doi.org/10.1016/j.inffus.2019.12.012
5. Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly*, *45*(3), 1433-1450. https://doi.org/10.25300/MISQ/2021/16274.
6. Bhave, D. P., Teo, L. H., & Dalal, R. S. (2020). Privacy at Work: A Review and a Research Agenda for a Contested Terrain. *Journal of management*, *46*(1), 127-164. https://doi.org/10.1177/0149206319878254
7. 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
8. Braun, V., & Clarke, V. (2019). *Successful qualitative research: A practical guide for beginners*. Sage.
9. Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: a review and research agenda. *The International Journal of Human Resource Management*, *33*(6), 1065-1097.
10. Castelvecchi, D. (2016). Can we open the black box of AI? *Nature News*, *538*(7623), 20-24.
11. Cheng, M. M., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review*, *31*(1), 100698. https://doi.org/10.1016/j.hrmr.2019.100698
12. Connelly, C. E., Fieseler, C., Černe, M., Giessner, S. R., & Wong, S. I. (2021). Working in the digitized economy: HRM theory & practice. *Human Resource Management Review*, *31*(1), 100762. https://doi.org/10.1016/j.hrmr.2020.100762
13. Cook, D. A., & Artino, J. A. R. (2016). Motivation to learn: an overview of contemporary theories. *Medical education*, *50*(10), 997-1014.
14. Davenport, T. H. (2014). *Big data at work: Dispelling the myths, uncovering the opportunities*. Harvard Business Review Press.
15. Equality Act 2010, GOV.UK (2010). https://www.gov.uk/guidance/equality-act-2010-guidance
16. Garcıa, J., & Fernández, F. (2015). A comprehensive survey on safe reinforcement learning. *Journal of Machine Learning Research*, *16*(1), 1437-1480.

17. Global Innovation Hubs. (2023). *Global Innovation Hubs Index 2023*. Retrieved 30th January from https://en.ncsti.gov.cn/services/index/cxzs_2023/
18. Hocken, E. (2023). *AI in recruitment: is it helping or hindering your drive for DE&I?* Retrieved 24 January from diversityq.com/ai-in-recruitment-is-it-helping-or-hindering-your-drive-for-dei/#:~:text=It%20is%20therefore%20unsurprising%20that,and%20freeing%20up%20employee%20time.
19. Hofeditz, L., Clausen, Rieß, A., Mirbabaie, M., & Stieglitz, S. (2022). Applying XAI to an AI-based system for candidate management to mitigate bias and discrimination in hiring. *Electronic Markets*(32), 2207-2233. https://doi.org/10.1007/s12525-022-00600-9
20. Hofeditz, L., Harbring, M., Mirbabaie, M., & Stieglitz, S. (2022). Working with ELSA - How an Emotional Support Agent Builds Trust in Virtual Teams. Proceedings of the 55th Hawaii International Conference on System Sciences, Hawaii.
21. Hofeditz, L., Mirbabaie, M., Luther, A., Mauth, R., & Rentemeister, I. (2022). Ethics guidelines for using ai-based algorithms in recruiting: Learnings from a systematic literature review. Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii.
22. Huang, C., Zhang, Z., Mao, B., & Yao, X. (2022). An Overview of Artificial Intelligence Ethics. *IEEE Transactions on Artificial Intelligence*, *4*(4), 799-819. https://doi.org/10.1109/TAI.2022.3194503
23. Huangshi, Y. Z., Long, L. W., & Wu, D. X. (2022). Opportunity and Challenges towards Happiness: Dobule-bladed Sword of Digital Human Resource Management. *Tsinghua Business Review*(9), 88-99.
24. Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature machine intelligence*, *1*(9), 389-399.
25. John-Mathews, J.-M., Cardon, D., & Balagué, C. (2022). From Reality to World. A Critical Perspective on AI Fairness. *Journal of business ethics*, *178*(4), 945-959. https://doi.org/10.1007/s10551-022-05055-8
26. Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business horizons*, *63*(1), 37-50. https://doi.org/10.1016/j.bushor.2019.09.003
27. Kshetri, N. (2021). Evolving uses of artificial intelligence in human resource management in emerging economies in the global South: some preliminary evidence. *Management Research Review*, *44*(7), 970-990. https://doi.org/10.1108/MRR-03-2020-0168
28. Kumar, R. (2012). Human resource information system: An innovative strategy for human resource management. *Gian Jyoti E-Journal*, *1*(2), 1-12.
29. Laurim, V., Arpaci, S., Prommegger, B., & Krcmar, H. (2021). Computer, Whom Should I Hire? – Acceptance Criteria for Artificial Intelligence in the Recruitment Process. Proceedings of the 54th Hawaii International Conference on System Sciences, Hawaii.
30. Li, L., Lassiter, T., Oh, J., & Lee, M. K. (2021). Algorithmic Hiring in Practice: Recruiter and HR Professional's Perspectives on AI Use in Hiring. AIES '21: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society, New York.
31. Lindebaum, D., Vesa, M., & Hond, F. d. (2020). Insights From "The Machine Stops" to Better Understand Rational Assumptions in Algorithmic Decision Making and Its Implications for Organizations. *Academy of management review*, *45*(1), 247-263. https://doi.org/10.5465/amr.2018.0181
32. Ma, C., & Ye, J. (2022). Linking artificial intelligence to service sabotage. *The Service Industries Journal*, *42*(13-14), 1054-1074. https://doi.org/10.1080/02642069.2022.2092615

33. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A Survey on Bias and Fairness in Machine Learning. *ACM Computer Survey*, *54*(6), Article 115. https://doi.org/10.1145/3457607
34. Mothukuri, V., Parizi, R. M., Pouriyeh, S., Huang, Y., Dehghantanha, A., & Srivastava, G. (2021). A survey on security and privacy of federated learning. *Future Generation Computer Systems*, *115*, 619-640. https://doi.org/10.1016/j.future.2020.10.007
35. Naseer, S., Raja, U., Syed, F., & Baig, M. U. A. (2021). When and why organizational cynicism leads to CWBs. *Personnel Review*, *50*(1), 90-107. https://doi.org/10.1108/PR-09-2019-0480
36. Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes*, *160*, 149-167. https://doi.org/10.1016/j.obhdp.2020.03.008
37. Ochmann, J., & Laumer, S. (2019). Fairness as a determinant of AI Adoption in Recruiting: An interview-based study. Diffusion Interest Group In Information Technology 2019 Proceedings,
38. Otley, D. (1999). Performance management: a framework for management control systems research. *Management Accounting Research*, *10*(4), 363-382. https://doi.org/10.1006/mare.1999.0115
39. Peng, J. F. (2023). Impacts and Challenges of New-generation Artificial Intelligence on Organization and Human Resource Management. *Human Resources Development of China*, *40*(7), 8-14.
40. Radonjić, A., Duarte, H., & Pereira, N. (2022). Artificial intelligence and HRM: HR managers' perspective on decisiveness and challenges. *European Management Journal*, *42*(1), 57-66. https://doi.org/10.1016/j.emj.2022.07.001
41. Raghavan, M., Barocas, S., Jon, K., & Levy, K. (2020). Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices. ACM Conference on Fairness, Accountability, and Transparency (FAT*),
42. Rathi, R. (2018). Artificial intelligence and the future of hr practices. *International Journal of Applied Research*, *4*(6), 113-116.
43. Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review*, *33*(1), 100925. https://doi.org/10.1016/j.hrmr.2022.100925
44. Ryan, M., & Stahl, B. C. (2020). Artificial intelligence ethics guidelines for developers and users: clarifying their content and normative implications. *Journal of Information, Communication Ethics in Society*, *19*(1), 61-86.
45. Safari, A., & Saleh, A. S. (2020). Key determinants of SMEs' export performance: a resource-based view and contingency theory approach using potential mediators. *Journal of Business & Industrial Marketing*, *35*(4), 635-654. https://doi.org/10.1108/JBIM-11-2018-0324
46. Siau, K., & Wang, W. (2020). Artificial intelligence (AI) ethics: ethics of AI and ethical AI. *Journal of Database Management*, *31*(2), 74-87.
47. Suen, H.-Y., Chen, M., & Lu, S.-H. (2019). Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? *Computers in Human Behavior*, *98*(September), 93-101. https://doi.org/10.1016/j.chb.2019.04.012
48. Sühr, T., Hilgard, S., & Lakkaraju, H. (2020). Does Fair Ranking Improve Minority Outcomes? Understanding the Interplay of Human and Algorithmic Biases in Online Hiring. Proceedings of the AAAI/ACM Conference on AI, Ethics, Society,

49. Swartz, T. H., Palermo, A.-G. S., Masur, S. K., & Aberg, J. A. (2019). The Science and Value of Diversity: Closing the Gaps in Our Understanding of Inclusion and Diversity. *The Journal of Infectious Diseases*, *220*(Supplement_2), S33-S41. https://doi.org/10.1093/infdis/jiz174
50. 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
51. Thompson, K. (2004). *The Early Sociology of Management and Organizations* (K. Thompson, Ed. 3rd ed., Vol. 1). Routledge.
52. Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: implications for recruitment. *Strategic HR Review*, *17*(5), 255-258. https://doi.org/10.1108/SHR-07-2018-0051
53. Wang, J., Shu, T., Zhao, W., & Zhou, J. (2022). Research on Chinese consumers' attitudes analysis of big-data driven price discrimination based on machine learning. *Frontiers in Psychology*, *12*, 803212.
54. Yarger, L., Cobb Payton, F., & Neupane, B. (2020). Algorithmic equity in the hiring of underrepresented IT job candidates. *Online Information Review*, *44*(2), 383-395. https://doi.org/10.1108/OIR-10-2018-0334
55. Yu, X., Xu, S., & Ashton, M. (2023). Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective. *Information Technology & People*, *36*(1), 454-474. https://doi.org/10.1108/ITP-04-2021-0254
56. Zhang, Q., Zhang, M., Guo, Z. H., & Zhang, A. Q. (2023). Research on Optimizaiton of Human Resource Scheduling Based on Artificial Intelligence Technology. *Microcomputer Applications*, *39*(3), 83-86. https://doi.org/1007-747X(2023)03-0083-04
57. Zhang, Y., Wu, M., Tian, G. Y., Zhang, G., & Lu, J. (2021). Ethics and privacy of artificial intelligence: Understandings from bibliometrics. *Knowledge-Based Systems*, *222*, 1-32. https://doi.org/10.1016/j.knosys.2021.106994
58. Zhang, Y. C., Xu, S., Zhang, L., & Yang, M. (2021). Big data and human resource management research: An integrative review and new directions for future research. *Journal of Business Research*, *133*, 34-50. https://doi.org/10.1016/j.jbusres.2021.04.019
59. Zwetsloot, R. (2020). China's Approach to Tech Talent Competition: Policies, Results, and the Developing Global Response. *Global China*(April), 1-19.