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An interdisciplinary review of AI and HRM: Challenges and future directions

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ABSTRACT

Artificial intelligence (AI) has the potential to change the future of human resource management (HRM). Scholars from different disciplines have contributed to the field of AI in HRM but with rather insufficient cross-fertilization, thus leading to a fragmented body of knowledge. In response, we conducted a systematic, interdisciplinary review of 184 articles to provide a comprehensive overview. We grouped prior research into four categories based on discipline: management and economics, computer science, engineering and operations, and others. The findings reveal that studies in different disciplines had different research foci and utilized different methods. While studies in the technical disciplines tended to focus on the development of AI for specific HRM functions, studies from the other disciplines tended to focus on the consequences of AI on HRM, jobs, and labor markets. Most studies in all categories were relatively weak in theoretical development. We therefore offer recommendations for interdisciplinary collaborations, propose a unified definition of AI, and provide implications for research and practice.

1. Introduction

Artificial intelligence (AI) is among the most influential technologies changing the labor market (e.g., Huang & Rust, 2018). On the one hand, AI can have negative consequences, such as eliminating over 45% of all jobs (Berg, Buffie, & Zanna, 2018) and increasing social inequality (e.g., Levy, 2018). On the other hand, it may also provide benefits, such as upgrading or augmenting jobs instead of replacing them (e.g., Autor, 2015). Taken together, it is fair to say that AI will have a significant impact on the future of human resource management (HRM), and the application of AI in HRM has great potential (Malik, Budhwar, Patel, & Srikanth, 2020; Malik, De Silva, Budhwar, & Srikanth, 2021).

AI-HRM is a topic beyond the field of HRM because of its interdisciplinary nature, i.e., the development of AI-based HR tools depends on progress in technical fields, while implementations of such AI tools and consequences of AI implementations rely on knowledge from social science. Scholars from various disciplines have contributed to AI–HRM knowledge. For example, computer science (CS) scholars developed AI algorithms to solve HRM problems (e.g., Anandarajan, 2002). Economists discussed AI's impacts on labor markets (e.g., Berg et al., 2018). Psychologists found that AI usage did not demotivate job candidates during recruitment (Van Esch, Black, & Ferolie, 2019) but might induce higher employee turnover (e.g., Brougham & Haar, 2020). Medical scholars revealed that medical employees were not ready for AI usage (e.g., Abdullah & Fakieh, 2020). Although substantial research exists on AI-HRM

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topics in various disciplines, each discipline approached the topic from a different perspective, paying little attention to synthesizing interdisciplinary knowledge. This is unfortunate because interdisciplinary knowledge and collaboration are particularly important for successful AI implementation (Fountaine, McCarthy, & Saleh, 2019) and talent development in the AI era (Pejic-Bach, Bertoncel, Meško, & Krstić, 2020). In response to this gap, a comprehensive interdisciplinary review can help synthesize the rather scattered knowledge and encourage disciplinary cross-fertilization by reducing misunderstanding and avoiding "reinventing the wheel."

Therefore, our research provides a large-scale, state-of-the-art, interdisciplinary systematic review of AI in HRM. The study intends to make the following contributions. First, we provide a comprehensive overview of the extant literature, thus synthesizing research from different disciplines and opening new avenues for future research. Second, we critically evaluate the theoretical foundations of the extant literature and provide suggestions for potential theoretical progress in AI-HRM. The evaluation and discussion of theoretical foundations are particularly important for the emerging field of AI-HRM, where scholars in certain disciplines, such as healthcare and CS, typically pay little attention to theories. Third, we critically evaluate the methodological rigor of the extant literature and offer examples of advanced AI methods for future management study. As different disciplines pursue different research methods, our interdisciplinary method evaluation may inspire future researchers to borrow methods from different disciplines, e.g., management scholars might apply CS methods, thus allowing for better analysis of AI-HRM studies.

2. Methods

The term "artificial intelligence" has a fuzzy definition, as it may refer to different things (Willcocks, 2020). Although we could not find a unified definition in prior literature, we set a broad scope of AI in the research before searching and analyzing the literature. Here, we focused on contemporary AI, which led to two principles. First, "contemporary" meant that we focused on advanced and smart AI, which can process massive computation and solve rather complicated real-world problems (e.g., Nilsson, 2010). Therefore, we excluded studies on non-contemporary AI (i.e., less-advanced artifacts) such as personal computers. Second, we only focused on AI, excluding studies on general technological changes such as studies of technological disruptive and Industry 4.0. We followed the principles to search and select literature. Fig. 1 shows our search process.

2.1. Searching literature

The study followed systematic review procedures (Tranfield, Denyer, & Smart, 2003) which fit well with our research purpose to keep the research breadth and increase the research reliability. We collected 41,831 articles from Social Sciences Citation Index and Sciences Citation Index databases through World of Science (WOS), as these are among the most comprehensive and popular databases for peer-reviewed journal articles. The vague AI definition makes it difficult to generate a comprehensive collection of interdisciplinary literature through a simple search. Therefore, we conducted three independent searches with different constraints and generated three sets of literature to increase the inclusiveness of the review. We searched for articles and reviews in English from 1990 to 2020 (including early access papers). We decided to focus on the period after 1990, because contemporary AI was powered by the advances of computer hardware and thus became reality only after early 1990s, owing to the birth of supercomputers with thousands of processors (e.g., Haenlein & Kaplan, 2019).

For the first round of literature search, we minimized constraints. We used the broad search parameter as "artificial intelligence" and covered all journals in all disciplines to collect a set of 23,761 papers. For the second round of literature search, we applied more constraints. We created detailed search parameters incorporating both AI and HRM. For AI parameters, we adopted the search terms in

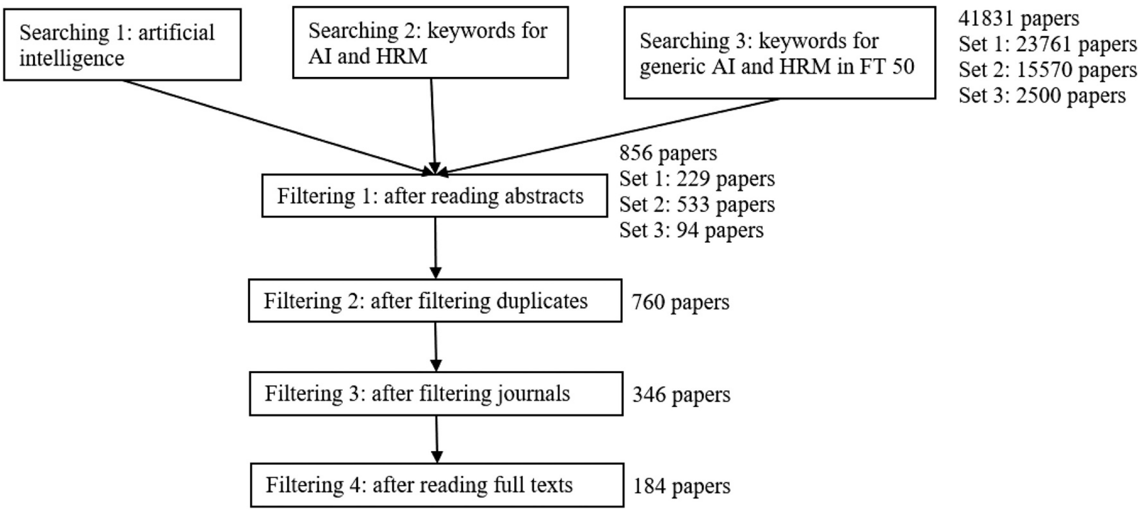

Fig. 1. Process of literature search and selection.

a systematic review of AI in medical contexts (Senders et al., 2018). We made two minor changes: 1) deleted two terms, i.e., "boosting" and "naive bayes," due to overlap and over-generalization; 2) added "robot*," according to AI-HRM literature's preferences (e.g., Berg et al., 2018). For HRM parameters, we adopted and combined terms from two interdisciplinary systematic reviews of HRM studies (Garcia-Arroyo & Osca, 2019; Voegtlin & Greenwood, 2016). We made two minor changes: 1) deleted "work" due to over-generalization; 2) added "labor, labour, job*," according to AI-HRM literature's preferences (e.g., Acemoglu & Restrepo, 2020). We used the following search terms and covered all journals in all disciplines to collect a set of 15,570 papers:

AI = (machine learning OR artificial intelligence OR natural language processing OR neural network OR support vector* OR random forest* OR deep learning OR Bayesian learning OR machine intelligence* OR computational intelligence OR computer reasoning OR robot*).*

HRM = (HRM OR human resource OR personal OR employ* relation* OR labor OR labour OR job*).*

For the third round of literature search, we added further constraints. We focused on Financial Times (FT) 50 journals, which represented high-quality management publications. Because management scholars may use generic terms to refer to AI, we added "algorithm*" as an extra AI parameter to increase the literature inclusiveness. However, we decided to exclude terms like "automation" or "digitalization," because they are too generic to distinguish AI with other information technology. We used the same HRM terms and the slightly extended AI terms to search all papers in FT50 journals. This resulted in a set of 2500 papers.

2.2. Selecting literature

During the literature selection, we applied a principle called "presumption of inclusiveness," i.e., we kept the paper if we could not know whether AI involved in the paper due to the use of generic terms (such as digitalization). We followed the rule to reduce the selection difficulties brought by the fuzzy definition of AI.

We implemented four steps in literature filtering. First, we read abstracts of all 41,831 papers and excluded papers that were clearly irrelevant to HRM or AI, leaving us with 856 papers. Second, we deleted duplications, leaving us with 760 papers. Third, we selected papers based on journal quality and only kept papers in FT50 and WOS Quarter 1 journals, leaving us with 346 papers. For inter-disciplinary journals with multiple intradisciplinary rankings, we applied the following two rules to sort them: 1) management had the highest priority in sorting, and computer science (CS) had the second-highest priority, followed by healthcare, then by engineering, and others (i.e., management > CS > healthcare > engineering > others). Management enjoyed the highest priority, because we mainly aimed to contribute to the management field, and AI is a CS intensive topic, so the CS came the second. Healthcare and engineering were two disciplines with the largest numbers of subdisciplines, so we created the superordinate category for journals in subdisciplines. For example, the engineering category included civil engineering, construction engineering, and so forth. There was little overlap between healthcare and engineering, so the rank between the two was a convenience rank to distinguish them from others; 2) others followed the discipline which had the highest number of journals, because the dominating fields were prioritized. In the last step of literature filtering, we read full texts of the remaining 346 papers and further excluded papers that were irrelevant to AI or HRM according to the paper contents, leaving us with 184 papers. During this step, we mainly excluded three types of papers: 1) AI-related papers in other management fields, particularly in corporate strategy domain; 2) AI-related papers in manufacturing floor shop schedules, because they focused on manufacturing rather than HRM, despite of their loose connections with employee staffing; 3) HRM-related papers with focuses on other technologies (e.g., mobile phones, etc.), which indicated no AI function.

The remaining 184 papers were the basis of our review. The papers came from 93 journals, covering 18 WOS disciplines (see Table 1). Table 2 shows all journals that published three or more papers related to AI-HRM.

2.3. Analyzing literature

We sorted papers into three sets of categories according to three deductive criteria. The first criterion was discipline. We sorted papers in 18 disciplines into four categories according to disciplinary closeness and the number of papers in each discipline. Therefore, we could still show the disciplinary differences while reduced the complexity of finding presentations. The CS (computer science) discipline was large enough to stand alone as an independent category. We combined engineering with operation disciplines to create the EO (engineering & operation) category and combined management with economics disciplines to create the ME (management & economic) category. Other disciplines formed the OT (other) category, in which 43% ($n = 15$) of papers belonged to the healthcare

Table 1
Number of papers in different disciplines.

	Discipline	Paper num.		Discipline	Paper num.
1	Management	59	11	Area study	1
2	Computer science	48	12	Communication	1
3	Economics	17	13	Environmental studies	1
4	Healthcare	15	14	Hospitality	1
5	Operations	14	15	Multidisciplinary sciences	1
6	Engineering	11	16	Neurosciences	1
7	Psychology	5	17	Sociology	1
8	Social science, interdisciplinary	3	18	Statistics	1
9	Law	2			
10	Social issue	2			

Table 2
Journals with three or more publications.

Rank	Journal	Number of papers
1	*Operations Research*	11
2	*Expert Systems with Applications*	9
2	*Management Science*	9
4	*IEEE Access*	8
5	*Journal of Applied Psychology*	5
5	*Production and Operations Management*	5
5	*Technological Forecasting and Social Change*	5
8	*Cambridge Journal of Regions Economy and Society*	4
8	*Computers & Industrial Engineering*	4
8	*Harvard Business Review*	4
8	*Journal of Medical Internet Research*	4
8	*Journal of the American College of Radiology*	4
13	*Big Data & Society*	3
13	*Computers in Human Behavior*	3
13	*Decision Support Systems*	3
13	*European Journal of Operational Research*	3
13	*Information & Management*	3
13	*MIT Sloan Management Review*	3
13	*Organizational Research Methods*	3
13	*Safety Science*	3

discipline. Fig. 2 shows different sizes of each category, indicating that ME is largest category, followed by CS, OT, and EO.

The second criterion was the nature of study. We sorted papers into either the empirical or conceptual category. The empirical category included papers that used empirical data to develop their studies. It also included papers that did not use empirical data but tested their developed models or algorithms in empirical settings. The conceptual category included papers that did not use empirical data nor test their studies in empirical settings. Empirical settings referred to real-life situations and environments. We considered empirical settings different from computer simulations that imitated the real-life situations. Thus, we sorted papers with only mock data from simulations into the conceptual category. Fig. 3 shows that most papers are empirical, with the highest ratio of empirical papers in CS (85%, $n = 41$), and the least ratio in EO (64%, $n = 16$).

The last criterion was the HRM function which a paper covered. We followed the conventional HRM functions to set the following categories: recruitment, performance & engagement, training, staffing, turnover, and employee well-being. Some HRM topics were not related to specific functions, such as unemployment or ethical HRM. Therefore, we sorted papers with general HRM issues into the "general" category. Consequently, the HRM function codes allowed us to have seven categories based on the focused HRM topics, which we will discuss in detail later.

3. Findings of systematic literature review

Fig. 4 shows the trend of publications over time from 1990 to 2020. Scant research had been published until 2016. However, the AI-HRM field has grown significantly since then. Notably, scholars from less-technical fields seem to contribute most for the development of the field, as indicated by the rapidly growing number of papers in ME and OT categories since 2017. On the other hand, scholars in the rather technical fields (i.e., CS and EO domains) seem to be less interested in AI-HRM topics, especially for those in the engineering and operation fields, as indicated by the slow growth of publications in the EO category. It was not surprising to find the aforesaid patterns of publication growth, considering that Google's Alpha Go defeated the human Go master Lee Sedol in 2016. The milestone event of AI development certainly attracted great attention toward contemporary AI from nontechnical communities. Giving the trend of publications, we believe the field of AI-HRM is likely to enjoy rapid growth in the coming years. The following sections discuss the topic coverage of the field and critically evaluate extant literature from the theoretical and methodological perspectives.

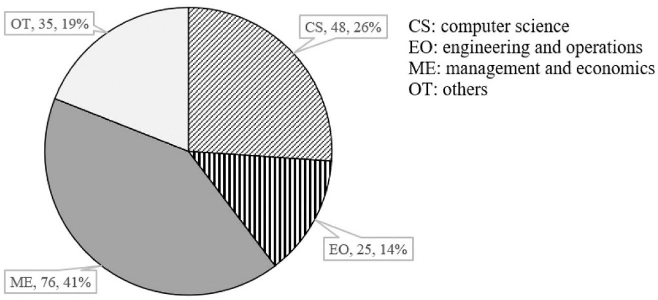

Fig. 2. Pie charts of disciplinary categories.

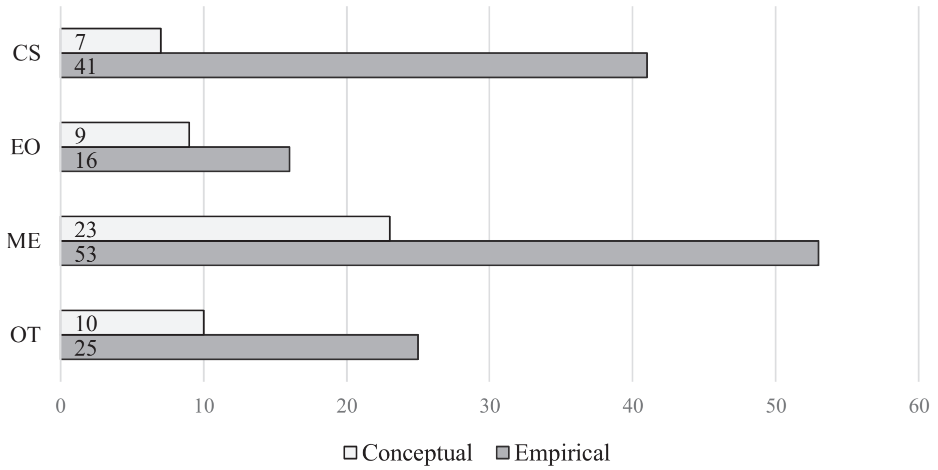

Fig. 3. Numbers of conceptual and empirical papers by disciplinary categories.

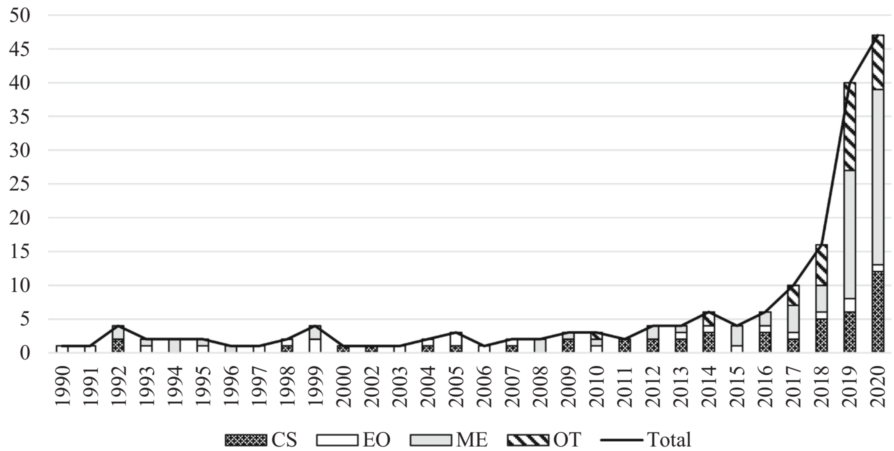

Fig. 4. Twenty-year trend of publications by disciplinary categories.

3.1. *Topic coverage*

Table 3 provides an overview of our deductive analysis of HRM functions covered in prior research. It becomes apparent that recruitment, performance, and staffing received the most attention, especially in the CS, ME, and EO domains, while employee training and well-being attracted less academic interest. General HRM topics also attracted great attention, especially from disciplines with less technical features (i.e., ME and OT domains). Among general HRM topics, most papers focused on AI's impacts on jobs, namely, on technological unemployment and future of work (see Table 4). Technological unemployment, which refers to the loss of jobs brought by the technology development, is a widely used term in prior research (e.g., Acemoglu & Restrepo, 2020; Granulo, Fuchs, & Puntoni, 2019). The following offers a closer look at the topics in each disciplinary category.

Topics in CS papers. Most papers in computer science aimed to develop AI tools rather than understanding managerial phenomena. Therefore, their main contributions were on the technical progress of HRM-related AI tools. As shown in Table 3, while CS papers

Table 3
Numbers of papers by HRM functions and disciplinary categories.

	Recruitment	Performance & engagement	Training	Staffing	Turnover	Employee well-being	General
CS	17	10	2	4	4	1	10
EO	2	4	2	14		3	
ME	3	14	4	9	8	1	37
OT	4	2			1	3	25
Total	26	30	8	27	13	8	72

Table 4
Topics of interests for papers in the general HRM category.

	CS	ME	OT	Total
Technological unemployment*	2	23	12	37
Future of work	2	5	5	12
Employee readiness for AI		4	4	8
Ethical issues	2	2	3	7
Labor market	4	1	1	6
Implementation of AI in HRM		2		2
	10	37	25	72

* i.e., unemployment brought by the development of technology.

covered all HRM functions, the HR recruitment (35%, $n = 17$) was the most popular topic, particularly in the recent decade ($n = 14$). Most CS papers in recruitment focused on technical development of AI tools to augment the recruitment efficiency ($n = 14$). Some developed AI tools to facilitate job-candidate matching ($n = 6$) according to candidates' previous job-seeking behavior (Benabderrahmane, Mellouli, & Lamolle, 2018) and candidates' characteristics (e.g., Faliagka et al., 2014). Others developed AI tools to facilitate candidate selection ($n = 4$), either by predicting candidates' future performance (Delgado-Gómez, Aguado, Lopez-Castroman, Santacruz, & Artés-Rodriguez, 2011) or benchmarking candidates with recruited employees (e.g., Khosla, Goonesekera, & Chu, 2009). Meanwhile, several scholars developed AI tools to facilitate interviews through detecting candidates' personalities (Jayaratne & Jayatilleke, 2020; Suen, Hung, & Lin, 2019).

Although above findings indicated notable technical progresses in AI recruitment tools, we found insufficient discussion of tool implementations. Only three CS papers focused on the effectiveness and ethic of developed recruitment tools, indicating significant research gaps. While technical evidence suggested that AI could perform similarly with human experts in making recruitment decisions (Hooper, Galvin, Kilmer, & Liebowitz, 1998) and predicting candidates' communication skills and personalities (Suen, Hung, & Lin, 2020), it also indicated that recruitment AI had invalid response to address bias in training data and, thus, were likely to replicate bias in recruitment and discriminate ethnical minorities (Köchling, Riazy, Wehner, & Simbeck, 2021). Interestingly, scholars from the ME domains confirmed the aforesaid technical invalidity of AI in ethical recruitment with the empirical evidence of discriminative AI (Lambrecht & Tucker, 2019), while scholars from the OT domains argued against the assumption of AI discrimination in recruitment (e.g., Suen, Chen, & Lu, 2019). The interdisciplinary inconsistency uncovered the insufficient validation of recruitment AI tools and opened a strong call for future interdisciplinary collaboration.

Topics of HR performance and engagement became the second most popular ($n = 10$), particularly in the recent two decades ($n = 9$). Similar to CS papers in recruitment topics, most performance and engagement papers focused on technical progress. Some papers developed AI tools to detect, evaluate, and categorize employee performance based on different criteria, such as employee fatigue (Carneiro, Pimenta, Neves, & Novais, 2017), multi-source evaluation scores (Góes & De Oliveira, 2020), or employees' work efficiency and development potential (e.g., Lukovac, Pamučar, Popović, & Đorović, 2017). Others developed AI tools to detect and predict employee engagement attributes such as employees' job satisfaction (Tung, Huang, Chen, & Shih, 2005), internet usage behavior (Anandarajan, 2002), so that AI could possibly provide early warnings of HR engagement failures such as employee misconducts, complaints, and so forth (Li, 2019).

Relatively less CS papers focused on topics of other HRM functions. All staffing papers ($n = 4$) developed AI tools to arrange work shifts in the contexts of medical industry, primarily based on workload, employee availability, and fairness (e.g., Valouxis & Housos, 2000). All turnover papers ($n = 4$) developed AI tools to find and predict patterns of employee turnover, from macro-level employee mobility in the labor market (e.g., Xu, Yu, Yang, Xiong, & Zhu, 2019), to micro-level employee turnover possibilities (e.g., Fan, Fan, Chan, & Chang, 2012). In addition, two papers developed AI tools to facilitate employee training (e.g., Lin, Wang, Wu, & Ye, 2011). Only one conceptual paper focused on employee well-being, proposing a system to predict workplace injuries (McCauley-Bell & Badiru, 1992).

Around 20% CS papers ($n = 10$) covered general HRM topics. Four of them developed algorithms to analyze labor market characteristics, such as predicting unemployment rates (Li, Xu, Zhang, & Lau, 2014) and clustering occupational groups (e.g., Boselli, Cesarini, Mercorio, & Mezzanzanica, 2018). When it comes to AI's impacts on the workforce, the CS domain seems to be rather optimistic. Willcocks (2020) criticized the anxiety toward AI-induced unemployment and argued that AI was likely to restructure jobs instead of fully substituting labor due to technological and social limitations. Similarly, Doraiswamy, Blease, and Bodner (2020) confirmed that medical physicians expected AI to change their job tasks instead of eliminating job positions, although female and US-based physicians felt more insecure. Several scholars extended the discussion to skill portfolios in the AI era. They found that future jobs preferred soft skills (Fareri, Fantoni, Chiarello, Coli, & Binda, 2020) and interdisciplinary knowledge (Pejic-Bach et al., 2020). Surprisingly, only Robert, Pierce, Marquis, Kim, and Alahmad (2020) comprehensively discussed fairness pitfalls in designs of AI algorithms for managing employees and proposed responding solutions, indicating the insufficient efforts of promoting AI fairness in the CS domain.

Topics in EO papers. Similar to the CS domain, the EO domains also had strong technical features, primarily contributing to technical developments of HRM-relevant AI tools. Table 3 shows that staffing was the most popular topic in the EO domains (56%, $n = 14$). All staffing papers developed AI tools to arrange employee work schedules mostly according to staff availability, skills, and task requirements (e.g., Shimomura, Kimita, Tateyama, Akasaka, & Nemoto, 2013). Therefore, staffing papers were rather similar with each other, although scholars applied different techniques and contexts. Most staffing papers ($n = 13$) developed tools in specific contexts, and their interested industry changed over time. During 1995 to 2003, EO papers focused on staffing tools in transportation sectors ($n = 5$, e.g., Caprara, Toth, Vigo, & Fischetti, 1998). In the recent two decades, EO papers were more interested in staffing tools in service ($n = 5$, e.g., Shimomura et al., 2013), healthcare ($n = 2$, e.g., Kim & Mehrotra, 2015), and military sectors (Holder, 2005).

Other EO papers covered diverse HR topics with the primary focus of technical developments, excluding turnover and general HRM topics. Performance-related EO papers ($n = 4$) developed AI tools to evaluate various HR performance criteria such as employee decision quality (Geva & Saar-Tsechansky, 2021), work efficiency (Azadeh & Zarrin, 2016), and skill proficiency (Tervo, Palmroth, & Koivo, 2010). Recruitment-related EO papers ($n = 2$) developed AI tools to facilitate job interview arrangements in career fairs (Bartholdi III & McCroan, 1990) and simulate different recruitment strategies in the job market (Chaturvedi, Mehta, Dolk, & Ayer, 2005). Training-related EO papers ($n = 2$) developed AI tools to arrange training schedules according to training availability and employees' needs (e.g., Qi, Bard, & Yu, 2004). Interestingly, employee-well-being-related EO papers ($n = 3$) focused on the construction industry, either proposing conceptual designs of AI-based safety management systems in construction sites (e.g., Kontogiannis & Kossiavelou, 1999), or investigating the influences of site arrangements on construction workers' perceptions toward robots (You, Kim, Lee, Kamat, & Robert Jr, 2018). Findings suggested that human-robot separated sites increased workers' perceived safety in robotic tasks.

Topics in ME papers. In the ME domains, nearly half the papers ($n = 37$) focused on general HRM topics. Technological unemployment was the most popular topic ($n = 23$), particularly from the macro-level perspective ($n = 21$). Since 2015, scholars demonstrated complex and often mixed attitudes and beliefs toward AI-induced unemployment. While many scholars argued that AI reduced employment, decreased average wage, and increased wealth inequality (e.g., Berg et al., 2018; Blanas, Gancia, & Lee, 2019; Camiña, Díaz-Chao, & Torrent-Sellens, 2020), they also agreed that AI raised the demand for highly skilled workers (Blanas et al., 2019) and will enhance future employment (Camiña et al., 2020) and income (Berg et al., 2018), although it can "easily take generations" to achieve the long-term benefits (Berg et al., 2018). Some scholars went further to investigate the victims of AI-induced unemployment. Pettersen (2019), for example, argued that AI can hardly replace knowledge workers, because the latter requires unprogrammable complex problem-solving to deal with situations without generic rules. It seems that AI is more likely to threaten low-skilled and less-educated employees, especially in manufacturing sectors (e.g., Blanas et al., 2019; Levy, 2018) and countries with less favorable economic conditions (Dekker, Salomons, & Waal, 2017). Consequently, the diffusion of AI may lead to politic populism because the current modest but visible job polarizing will boost populist candidates who pit "the people" with low-pay and low-skills against "the elite" with high-pay and high-skills (Levy, 2018).

In contrast, there were neutral or optimistic opinions. Autor (2015), for example, argued that media and experts overstated the extent of technological unemployment and ignored the possibility of automation to increase productivity, raise earnings, and create new jobs. Furthermore, many scholars argued that AI-induced technological unemployment will be a relatively slow process, because AI initially replaces humans in performing tasks instead of entire jobs (e.g., Huang & Rust, 2018; Levy, 2018). Huang and Rust (2018) argued that AI can only replace humans gradually through four stages based on the complexity of job tasks and the limited ability of AI. Although AI is eliminating analytical tasks, it will take time for AI to replace job tasks that require interpersonal and empathetic skills (Huang & Rust, 2018; Huang, Rust, & Maksimovic, 2019). Meanwhile, scholars proposed that humans have control over AI-induced unemployment, particularly through intervention policies (Kim, Kim, & Lee, 2017) because automation will not be fully implemented due to social-economic-political constraints such as cultural acceptance and political preference (Fleming, 2019).

In ME papers that focused on impacts of AI on future jobs ($n = 5$), scholars found that AI could have either negative or positive influences, depending on different job designs (e.g., Sampson, 2021). Primarily, AI changed job structures. Empirical evidence found that the use of robots in pharmacy works reconfigured boundaries among different occupational groups, and such changes had implications for future jobs in many aspects (Barrett, Oborn, Orlikowski, & Yates, 2012). Apart from job reconfiguration, AI also created new jobs. Wilson, Daugherty, and Bianzino (2017) introduced three types of new jobs, i.e., trainers, explainers, and sustainers, which emerged to train, explain, and keep the effective and responsible operation of AI. Consequently, scholars called for governmental policies to encourage the positive and reduce the negative impacts of AI on future jobs (Waring, Bali, & Vas, 2020).

Overall, most ME scholars argued that most employees were not ready for AI usage, and they encouraged companies to achieve the greatest benefits of AI via AI–employee integration, job redesign, and employee training (e.g., Barro & Davenport, 2019). They further suggested that socio-technical factors, such as open-mindedness culture, were crucial in successful AI–employee integrations (Makarius, Mukherjee, Fox, & Fox, 2020; Xu, Stienmetz, & Ashton, 2020). Meanwhile, ME scholars seemed to be pessimistic regarding ethical AI usage. For example, Holford (2022) found that AI resulted in the distortion of ethical responsibility in aircraft operations by reducing pilots' power of control, while pilots still bear full liability for any crisis. Leicht-Deobald et al. (2019) argued that AI-based HR decisions increased compliance but reduced employee integrity, probably because employees had blind trust in AI processes and could hardly opt out of AI monitoring. The rather pessimistic arguments responded to challenges of using AI in HRM, namely, the complexity of HR phenomena, small data sets, ethical constraints, and employee reactions to AI-based decisions (Tambe, Cappelli, & Yakubovich, 2019).

For ME papers targeting specific HRM functions, employee performance and engagement attracted greatest research interests (18%, $n = 14$). Empirical evidence indicated that, although the use of AI could contribute to better performance and engagement (e.g., Gu, Deng, Zheng, Liang, & Wu, 2019), the benefits required preconditions such as increased employee control over machines (Wall, Jackson, & Davids, 1992), appropriate task practices (Beane & Orlikowski, 2015), and employees' adequate skills in CS and engineering (Choudhury, Starr, & Agarwal, 2020). Otherwise, the use of AI may be harmful for work performance (Beane & Orlikowski, 2015; Choudhury et al., 2020). Moreover, ME scholars suspected the effectiveness of AI in evaluating HR performance, which formed a sharp contrast with CS scholars who had a very positive evaluation of AI. Recent papers criticized the ethical pitfalls of AI in facilitating HR performance evaluations. Primarily, the AI-based HR performance evaluation neglected real working situations because AI made decisions only based on data, i.e., quantifiable and usually limited information (Newlands, 2020). Therefore, the AI evaluation was likely to make unethical and inaccurate conclusions due to the ignorance of employees' moral standards and emotions. Consequently, the AI-based HR performance evaluation could undermine employees' beliefs about procedural fairness (Newman, Fast, & Harmon, 2020).

Staffing was the second most popular functional topic in ME papers ($n = 9$), followed by turnover ($n = 8$). Similar to staffing papers in CS and EO domains, all ME papers in staffing developed AI tools for employee work schedule arrangements based on staff characteristics and task requirements, and most of them were contextually bounded. Scholars developed staffing tools in healthcare (Roth & Peranson, 1999), transportation (Hoffman & Padberg, 1993), and military sectors (Krass, Pinar, Thompson, & Zenios, 1994) during 1990 to 2000, and they changed the focus to service call centers from 2000 (e.g., Azriel, Feigin, & Mandelbaum, 2019). For turnover-related ME papers, most of them focused on rather methodological or technical topics, either promoting AI methods in HR turnover studies (e.g., Choudhury, Allen, & Endres, 2021) or developing AI tools to discover employee mobility, i.e., the macro-level turnover of labor (e.g., Liu, Pant, & Sheng, 2020). Nevertheless, several papers discussed AI's impacts on employee turnover, and suggested that AI usage increased employee turnover because of the routinization of tasks (Yuhong & Xiahai, 2020) and perceived threats of AI (Brougham & Haar, 2020; Li, Bonn, & Ye, 2019).

A relatively small number of ME papers covered topics in HR training ($n = 4$), recruitment ($n = 3$), and employee well-being ($n = 1$). In training-related ME papers, scholars depicted the hybrid influences of AI on future HR trainings. AI leverage required updates of HR training contents, since some skills, such as problem-solving, critical thinking, communication, and teamwork, were particularly crucial in the era of AI (Rampersad, 2020). Besides, AI could facilitate training effectiveness, for example, by offering personalized trainings for leaders with different management styles (Buckingham, 2012). Nevertheless, AI could also bring unexpected negative consequences. For example, Beane (2019a, 2019b) argued that the AI usage distorted training processes by reducing employees' opportunities to learn from legitimized informal training. Consequently, AI forced trainees to perform illegitimated yet tolerated behaviors at the edge of their capacity without supervision, to gain skills in informal trainings. The similar hybrid influences also existed in HR recruitment according to recruitment-related ME papers. For example, although AI was effective in evaluating job-seekers compared with human HR experts (Campion, Campion, Campion, & Reider, 2016), the AI-enabled job advertising exhibited gender discrimination (Lambrecht & Tucker, 2019). Cappelli (2019) further revealed several limitations of AI recruitment, namely, the little HRM knowledge of tool developers, invalidity of the developed tools, dynamic HR demands, risk of cheating behaviors, and insufficient training data, which were consistent with general challenges of using AI in HRM (Tambe et al., 2019). The only ME paper in employee well-being (Bromuri, Henkel, Iren, & Urovi, 2021) developed an algorithm to predict employee stress in service call centers.

Topics in OT papers. Most papers in other disciplines focused on rather general HRM topics (71%, $n = 25$), especially on AI-induced technological unemployment ($n = 12$). Different from ME domains, OT papers were more interested in the rather micro-level analysis of technological unemployment ($n = 10$). While five papers focused on AI-induced unemployment in the healthcare sector, their findings were inconsistent. Some scholars argued that AI replaced healthcare employees (Mazurowski, 2019), and most medical workers feared the possible replacement (Abdullah & Fakieh, 2020). Others believed that AI is unlikely to replace future medical employees (Blease et al., 2019; Recht & Bryan, 2017; Wright, 2019). Nevertheless, all scholars agreed that AI diffusion is an inevitable trend, which will bring great changes in healthcare jobs, although most employees were not ready for the challenges and need further training to use AI tools effectively and ethically (e.g., Abdullah & Fakieh, 2020; Blease et al., 2019). Other OT papers in technological unemployment were rather optimistic. Wajcman (2017), for example, criticized the pessimistic arguments around technological unemployment and argued for a more nuanced analysis of the political and social aspects of technology development. Furthermore, OT scholars argued that AI is unlikely to cause massive unemployment of creativity jobs due to insufficient rules and data in creative tasks (e.g., Hammershøj, 2019). Empirical evidence supported the aforesaid optimistic arguments. In the journalism sector, AI usage was a result of socio-technical-driven factors, and journalists could adapt to changes well to secure their jobs (Linden, 2017). In the music sector, audio mastering engineers worked with AI tools and considered AI as collaborators or assistants instead of competitors for jobs (Birtchnell, 2018). Interestingly, psychologist found contradictory individual attitudes toward AI-induced job loss. First, although people preferred general workers to be replaced by other humans, they preferred to lose out to AI instead of other humans in competition for their own jobs (Granulo et al., 2019). Second, people expressed more discomfort with AI replacement if the losing job required emotion and expressed reverse feelings if the job required cognition (Waytz & Norton, 2014).

OT scholars were also rather optimistic regarding AI's impacts on future jobs ($n = 5$). They argued that, although AI usage could lead to digital Taylorism with which machines routinized tasks and made human workers exchangeable in various tasks (Delfanti & Frey, 2021), the AI-induced job reconfigurations could contribute to decent work (Tuomi, Tussyadiah, Ling, Miller, & Lee, 2020), and the AI production processes could create a set of new jobs for “AI preparation, AI verification, and AI impersonation” (Tubaro, Casilli, & Coville, 2020), similar to opinions from Wilson et al. (2017) in ME domains. Nevertheless, it is difficult to measure the effects of AI on the future of work due to the insufficient knowledge of micro-level occupational insights such as the dynamic skill requirements of different jobs, and the insufficient understanding of interactions between AI and social mechanisms (Frank et al., 2019). Furthermore, most employees were not ready for future AI implementation in the medical industry ($n = 4$, e.g., Sandhu et al., 2020).

In accordance with above general HRM topics, OT papers were more optimistic for AI-related ethical issues compared with their counterparts in ME domains (e.g., Holford, 2022). Although employees perceived AI decisions less trustworthy than human decisions in managerial tasks, they considered AI decisions as fair as human decisions in mechanical tasks (Lee, 2018), and they reacted similarly to procedural justice of human or AI decisions (Ötting & Maier, 2018). In fact, robots even reduced discrimination by fostering a common human identity when intergroup differences between robot and human overrode human intragroup differences such as racial differences (Jackson, Castelo, & Gray, 2020).

A small number of OT papers covered topics in HR recruitment ($n = 4$), employee well-being ($n = 3$), performance ($n = 2$), and turnover ($n = 1$). Research revealed that AI recruitment tools did not reduce candidates' job apply intentions (Van Esch et al., 2019), and candidates perceived AI raters as fair as human raters in interviews (Suen, Chen, & Lu, 2019). In fact, AI interview raters indicated less appearance prejudice compared with human raters (Suen, Chen, & Lu, 2019). Scholars further provided suggestions against potential ethical pitfalls in AI recruitment, by proposing technical suggestions to avoid possible discrimination in AI-based job advertisements according to legal frameworks (Dalenberg, 2018) and suggesting a third-party data keeper to safeguard a rich and representative dataset of private information (Blass, 2019).

While some scholars developed AI tools to detect and predict workplace injuries (e.g., Cheng, Ng, Sin, Lai, & Law, 2020) or stress (Yan, Chien, Yeh, Chou, & Hsing, 2020), other OT papers focused on HR performance, engagement, and turnover in healthcare contexts. Findings suggested that, although AI was technically effective in evaluating employees' surgical skills (Richstone et al., 2010), the use of AI could change the division of labor, workflow, and performance in surgical teams under the influences of contextual factors such as team relationships (Randell et al., 2021). Other scholars developed an AI-based turnover predictor to estimate medical staff's length of stay (Moyo, Doan, Yun, & Tshuma, 2018). Taken together, the OT domain is rather optimistic toward AI leverage, although their empirical evidence might be limited to certain contexts.

3.2. *Evaluation of theory*

In this section, we review and evaluate the use of theory in prior AI-HRM research. In line with seminal papers (e.g., Corley & Gioia, 2011; Sutton & Staw, 1995), we considered a paper as theoretical sound if it justified 1) what was the conceptual model, 2) how, and 3) why the model should work. According to the above criteria, only 21% of reviewed papers built their studies on theories or theoretical constructs ($n = 39$, see appendix for further detail). Therefore, it is reasonable to conclude that the majority of AI-HRM research is relatively weak in theoretical development.

Theories in CS papers. Only 20% of CS papers ($n = 10$) used theories (see appendix for covered HRM functions). Personality theories were most popular in CS studies ($n = 6$), especially the big-five theory ($n = 4$). Probably due to disciplinary conventions, CS scholars were more interested in applying instead of extending theories, which limited their theoretical contribution. Exceptionally, Suen, Hung, and Lin (2019) and Suen et al. (2020) extended the big five theory by combining it with social information processing theory and social signaling theory, respectively. Other personality models included Myers-Briggs-Type-Indicator framework (Lee & Ahn, 2020) and HEXACO (Jayaratne & Jayatilleke, 2020). Although Lee and Ahn (2020) explained and justified their theoretical choice, both papers made little efforts to develop the applied theories.

For other theories, Lukovac et al. (2017) used the BCG matrix of corporate product categorization to sort employees by performance without the justification of adapting the BCG matrix in HRM performance categorization. Abubakar, Behravesh, Rezapouraghdam and Yildiz, (2019) integrated psychological ownership theory with social exchange theory but made a notable theoretical contribution to knowledge management instead of AI-HRM field because the paper was a method paper that used AI as a method in employee knowledge research. Nevertheless, as an encouraging example, Robert et al. (2020) systematically introduced organizational justice theory to the CS discipline and extended the theory to a fairness AI framework.

Overall, the CS domain was relatively weak in theoretical developments. Only some scholars applied social science theories, and most applied theories were rather generic and simple in conceptual designs. This was not surprising because the CS domain conventionally focused more on practical contributions. Nevertheless, the low representation of HRM theories further confirmed ME scholars' concerns of insufficient HRM knowledge foundation of developed AI tools (Cappelli, 2019), and thus may reduce the validity of the CS studies.

Theories in EO papers. Only 12% of EO papers ($n = 3$) used theories (see appendix for covered HRM functions). Similar to the CS domain, the EO domains were also rather practical oriented and paid less attention on theoretical development. For example, Kontogiannis and Kossiavelou (1999) used the tactical decision making under stress model (TADMUS), i.e., a theoretical model to understand decision-making, cooperation, and team adaptation under stress. The authors aimed to design a stress-free AI decision tool based on TADMUS, instead of extending the theoretical boundary of the model. Similarly, Chaturvedi et al. (2015) built their AI tool based on the first-generation labor supply model without further development of the model. Besides, as far as they described, the model was highly confined to recruitment in military contexts.

Nevertheless, You et al. (2018) made efforts in developing social science theories. They developed a theory called the robot acceptance safety model (RASM) to understand the relationship between individual perceived safety and use of robots. The RASM argued that team identification and trust regarding the robot can have an impact on the perceived safety associated with the collaborative task. Unfortunately, as a deductive and quantitative model, the RASM had insufficient theoretical validation from prior theories, and the authors used experiments with only 30 participants to validate the model. Therefore, although the RASM can be useful for AI-human collaboration research, the theory may require further validation to become established. According to the above evaluations, it is fair to conclude that the EO domains had noteworthy pitfalls in theoretical foundations and developments.

Theories in ME papers. Only 25% of ME papers ($n = 19$) used theories (see appendix for covered HRM functions). These theories are more diverse compared with theories in other domains. Notably, four papers proposed their own theories or theoretical constructs, making remarkable theoretical contributions. Huang and Rust (2018) conceptually developed a theory of AI job replacement, which demonstrated a four-stage model for AI's replacement of job tasks. Although the authors did not empirically validate the proposed theory, they provided empirical evidence for consistent concepts in another paper (Huang et al., 2019). With the similar interests on AI-job interface, Sampson (2021) developed a professional task-automation framework to describe potential influences of automation on different professional service and validated the framework with empirical data, and Fleming (2019) conceptually proposed a construct called “bounded automation,” which refers to the limited potential of automation due to the social-economic-political constraints. Besides, drawn on empirical observations, Beane (2019b) built a construct called “shadow learning” to account for individual illegitimated learning behaviors when AI reduces training opportunities.

Six papers used rather generic theoretical constructs (see appendix for more detail). Two of them extended boundaries of the applied constructs. Holford (2022) used a series of authority and control constructs to build conceptual arguments and contributed to a new understanding of used constructs in the AI era. Barrett et al. (2021) applied and extended Pickering's concept of “tuning” in their study of AI-shaped occupational boundaries. The tuning referred to an emergent and generative process of resistance, accommodation, and reconfiguration during the recursive diffusion of new technology when human plans, interests, and practices are entangled with technology. Others made little effort in extending the applied constructs. For example, Roth and Peranson (1999) used a construct in game theory as the underlying theoretical foundation for the design of a staffing tool, but they did not aim to contribute for the construct development.

Other papers used established theories in a more systematic and sophisticated way, although some still had relatively unclear positions in making theoretical contributions. For example, Newlands (2020) sophisticated applied Henri Lefebvre's spatial triad theory with unclear theoretical contribution. The spatial triad theory discusses different types of (material/social) spaces and their interactions. It further argues for the existence of a spatial triad composed of abstract representations of space (conceived space), habitual spatial practices (perceived space), and subjective representational space (lived space). Similarly, Xu et al. (2020) systematically applied organizational change theory, yet with ambiguous theoretical development. The theory argues that organizations must develop the ability to adapt continual changes in various ways.

On the contrary, some scholars made significant theory developments primarily through theoretical syntheses. Makarius et al. (2020), for example, integrated socio-technical systems theory with the organizational socialization framework to develop a model of AI-employee integration, which successfully extended the theoretical boundaries. The socio-technical systems theory highlights the interactions between social and technical factors in influencing the use of technologies, and the socialization framework can help explain the process of such social-technical influences. Similarly, Gu et al. (2019) integrated the performance-maintenance (PM) theory of leadership and media synchronicity theory. PM theory argues that employee performance and employee relationship maintenance are the two dimensions of leaders' behaviors. Media synchronicity theory argues that stronger media ability increases communication effectiveness by providing information synchronicity. The authors added group communication effectiveness from media synchronicity into the PM theory. Besides, Newman et al. (2020) used organizational justice theory with a particular focus on perceived procedure fairness. The authors contributed to the theory by showing the importance of human involvement in increasing perceived procedure fairness. Overall, the ME papers were better in theory development compared with others, and we will further discuss their potential contributions to future theoretical developments in later sections.

Theories in OT papers. Only 20% of OT papers ($n = 7$) used theories (see appendix for covered HRM functions). Notably, with empirical observations, Tuomi et al. (2020) developed a new theory called decent work through automation, which suggested that three factors, i.e., the effectiveness of human-machine cooperation, working conditions, and the level of empowerment, will determine AI's ability to provide decent work in the future.

Most of other papers were more interested in applying instead of extending theories. For example, Linden (2017) generically applied social construction of technology theory in the exploratory study. Social construction of technology argues that human actions shape technologies, so the diffusion of technology is embedded in its social contexts. Suen, Chen, and Lu (2019) applied social information processing theory, media richness theory, and social interface theory to build hypotheses. However, the authors offered insufficient explanation and synthesis of these theories, especially for the social interface theory. Jackson et al. (2020) applied social categorization theory with a particular reference to the common in-group identity model. Although the authors justified the existence of group identity in AI-human interactions, the paper put limited efforts in further extending the theory. Lee (2018) applied computers-are-social-actors (CASA) theory with unclear theoretical contributions. The theory posits that people consider computers as social actors, so they respond to computers according to the same socio-psychological principles in regular interpersonal interactions.

Nevertheless, evidence does exist for theoretical development. Ötting and Maier (2018), for example, integrated CASA theory with organizational justice theory and extended theoretical boundaries of CASA by validating the theory in contexts regarding procedural justice of decisions. Further, Randell et al. (2021) integrated boundary work construct with negotiated order theory. Boundary work refers to the construction of occupational boundaries. Negotiated order suggests that changes will lead to renegotiation of social orders. The authors introduced the renegotiation concepts into the boundary work to suggest a reproduction of professionals. Overall, the OT papers were relatively weak in theoretical contributions, but they still suggested theories with high potential.

3.3. Evaluation of method

Papers in different disciplines followed different research methods. Most papers in technical disciplines did not use methods that are conventional in the management field, because they aimed to build AI tools, and their method referred to the process of developing AI techniques. It is beyond the scope of this review to evaluate different AI techniques, so we will only briefly review the involved AI techniques. Meanwhile, 13 papers used AI as the research method in HRM studies; they provided valuable examples for future scholars to follow. Because no conceptual papers used any specific method, we will only evaluate methods in empirical studies in the following sections.

Methods in CS papers. In 41 empirical CS papers, 82% ($n = 34$) developed AI systems and did not apply conventional methods in social science. We evaluated their methods with the used techniques and quality of data. Although it is infeasible to compare all techniques in detail because scholars used a wide variety of techniques with different terms, AI-based HRM tools seemed to have rather complicated technical designs, since at least 26 papers used two or more named techniques to build their AI tools. The most popular technique was neural network ($n = 18$), followed by fuzzy clustering ($n = 9$) and natural language processing (NLP) ($n = 6$). The neural network, fuzzy clustering and NLP were overarching terms, referring to different branches of algorithms with similar functions. For data quality, 19 papers used secondary data to develop tools, in which most had large data size (e.g., Benabderrahmane et al., 2018) with only seven papers having data <10,000 samples. Eight papers developed tools by real-time tests or laboratory observations and provided limited information regarding the data quality (e.g., Carneiro et al., 2017). Seven papers used survey data (e.g., Góes & De Oliveira, 2020), but only two had over 1000 samples. Considering that AI algorithms usually require large-size training data, the small data size reduced the validity of the developed tools. Besides, probably constrained by domain knowledge, survey validity was problematic in some CS papers from social science perspectives. For example, Khosla et al. (2009) designed their own survey questions without proper scale validation and only provided Cronbach's alpha to justify the measurement reliability.

Four CS papers used conventional quantitative social science methods. Only Doraiswamy et al. (2020) used quantitative survey with a sufficient data size (samples>500), but their analyses were rather descriptive with only frequency-percentage results. Others used experimental methods (e.g., Suen et al., 2020). However, only Hinds, Roberts, and Jones (2004) had over 100 participants, and Hooper et al. (1998) also reported descriptive results, indicating method problems in data size and statistical rigor. Three CS papers promoted AI as a research method in HRM studies, including two neural networks to predict nonlinear relationships with survey data (Abubakar, Behravesh, Rezapouraghdam, & Yildiz, 2019; De Oliveira, Possamai, Dalla Valentina, & Flesch, 2013) and a combination of NLP and a hierarchical clustering algorithm with secondary data (Pejic-Bach et al., 2020). While the three papers encouraged HRM scholars to take advantage of AI methods, their data sizes were rather small for algorithmic analyses (samples < 10,000), and they had insufficient method validation, raising our concerns over method validity. Overall, most CS papers for technical development had relatively strong data sizes but weak survey quality, while other CS papers showed methodological disadvantages in general.

Methods in EO papers. In 16 empirical EO papers, 88% ($n = 14$) developed AI tools without the use of conventional social science methods, so we also evaluated them by used techniques and data quality. For techniques, five EO papers did not refer to the name of used techniques (e.g., Caprara et al., 1998). Others used diverse techniques such as neural network (e.g., Shimomura et al., 2013), random forest (Geva & Saar-Tsechansky, 2021), and so forth. Nevertheless, EO papers showed no preferences for any particular technique. For data quality, EO papers provided insufficient data information with secondary data ($n = 9$, e.g., Kim & Mehrotra, 2015) and real-time test data ($n = 3$, e.g., Tervo et al., 2010). Only Geva and Saar-Tsechansky (2021) provided detailed information for the used secondary data. Meanwhile, two papers used small size survey data to develop tools (e.g., Shimomura et al., 2013), but only Azadeh and Zarrin (2016) provided evidence of measurement validity. Besides, You et al. (2018) applied an experimental method with only 30 participants. Consequently, we considered the unjustified data quality as the main methodological problem in EO papers.

Methods in ME papers. In 53 empirical ME papers, most used conventional methods in social science ($n = 34$). It becomes apparent that ME scholars adored quantitative methods ($n = 28$). They primarily collected quantitative data from secondary sources ($n = 14$), surveys ($n = 8$), and experiments ($n = 5$). For papers with secondary data, only three confirmed large data sizes (samples>1000) (e.g., Leigh et al., 2020). Others did not report data details such as structure or size. Interestingly, all papers without detailed data information focused on macro-level analysis, particularly on technological unemployment (e.g., Berg et al., 2018). Papers of macro-level studies also suffered from the oversimplified assumptions in economic model buildings. For example, while empirical evidence indicated industrial and regional differences in robot adoption (e.g., Acemoglu & Restrepo, 2020; Gentili et al., 2020), some scholars assumed that robots equally influenced all industries and areas before building conceptual models (e.g., Leigh et al., 2020). Thus, these studies might involve variance bias.

For papers with survey data, only three papers had relatively small data size (sample < 200) (e.g., Rampersad, 2020). Compared with papers in other disciplines, ME papers had stronger methodological rigor in survey studies, usually with a series of validity techniques. However, some still indicated methodological pitfalls in measurement validity. For example, several scholars used the same scale to measure employee perceptions of AI usage (e.g., Brougham & Haar, 2020; Li et al., 2019). While some labelled the measure as perceived AI awareness (e.g., Li et al., 2019), underlying items indicate that the scale measures perceived threats of technologies (Brougham & Haar, 2020). Therefore, the inappropriate measurement of "AI awareness" could lead to misinterpretation of empirical phenomena and thus rise our concern of measurement external validity. For experimental studies, scholars tended to conduct "field tests" (Lambrecht & Tucker, 2019), which referred to unconventional field experiments in real industrial settings (e.g., Lambrecht & Tucker, 2019; Wall et al., 1992). Notably, Lambrecht and Tucker (2019) generated over one-million data through their "field test," which was an extremely large data size in social science experiments. Besides, Newman et al. (2020) also collected over 2400 samples by multiple rounds of experiments, with a combined data from employee, MTurk, and student participants.

Six qualitative ME papers used diverse approaches, including ethnography (Beane, 2019b), field study (Beane & Orlikowski, 2015), content analysis (Seeber et al., 2020), and Delphi method (Xu et al., 2020). Others did not justify a specific method. Except for studies with small-size open-answer surveys (Seeber et al., 2020; Xu et al., 2020), most qualitative studies had good data triangulations of interviews, personal observations, and secondary materials (e.g., Barrett et al., 2012; Beane, 2019b). Nevertheless, they provided insufficient data details of non-interview materials.

Nine ME papers focused on developing AI tools. Although scholars showed no preference for certain techniques, all of them used secondary data, including four with unclear data structure (e.g., Azriel et al., 2019), three with relatively insufficient data (e.g., Bromuri et al., 2021), and two with enough data for developing algorithms (Liu et al., 2020; Roth & Peranson, 1999). The other 10 papers promoted the AI method in HRM studies (e.g., Minbashian, Bright, & Bird, 2010). They demonstrated the ability of AI techniques to recognize patterns (e.g., Somers & Casal, 2009), cluster groups (e.g., Carton & Cummings, 2013), or predict future patterns (e.g., Spisak, van der Laken, & Doornenbal, 2019). The neural network was the most popular technique with four papers (e.g., Somers & Casal, 2009), followed by NLP with three papers (e.g., Campion et al., 2016). Scholars tried to rigorously use the new method, but they seemed to follow different standards, primarily due to the lack of a general methodological convention. For example, while Speer (2020) provided evidence to support the measurement validity of the NLP method, Prüfer and Prüfer (2020) did not offer similar method validity even with the similar method approach. Notably, the AI method encouraged the potential of data triangulations. Most papers with the AI method ($n = 7$) used secondary data from multiple sources with rather complicated structure or large size. For example, Choudhury et al. (2021) used various observations of 1191 employees for over 40 months, and Prüfer and Prüfer (2020) used data of over 7.7 million job advertisements.

Methods in OT papers. In 25 empirical OT papers, most ($n = 20$) used conventional methods in social science. Quantitative studies collected data from experiments ($n = 7$) and surveys ($n = 5$). Experimental studies came from psychology (e.g., Waytz & Norton, 2014), healthcare (Richstone et al., 2010) and neuroscience (Granulo et al., 2019) disciplines. Probably due to their disciplinary conventions of conducting experiments, most papers used rather complicated methods with multiple experiments to replicate and confirm findings (e.g., Granulo et al., 2019), excluding Suen, Chen, and Lu (2019) and Lee (2018). Consequently, papers with experimental methods had relatively large data size. Notably, three papers only had participants from Amazon MTurk (e.g., Lee, 2018). Considering the difficulty of control randomity with the MTurk approach, the data validity might be a problem to reduce method credibility. Meanwhile, most papers with a quantitative survey came from the healthcare discipline and were relatively descriptive (e.g., Abdullah & Fakieh, 2020), excluding Van Esch et al. (2019). The descriptive issue had two indicators. First, the authors used unjustified measurements and provided insufficient measurement validity (e.g., Collado-Mesa, Alvarez, & Arheart, 2018). Second, they used rather basic statistical methods to generate descriptive results (e.g., Abdullah & Fakieh, 2020). Although such "observational descriptive study" (Collado-Mesa et al., 2018) might be conventional in healthcare disciplines, the methodological problem still suggested limited reliability of survey studies in OT papers.

Eight OT papers used qualitative methods, including ethnography (Birtchnell, 2018; Randell et al., 2021; Wright, 2019), grounded theory, (Sandhu et al., 2020; Tuomi et al., 2020), and other unnamed qualitative approaches (e.g., Linden, 2017). Although three ethnographic studies had advantages in data triangulations, other qualitative studies suffered from method pitfalls, including insufficient data size (sample < 50) (e.g., Tuomi et al., 2020) and unclear data information (Tubaro et al., 2020). Besides, five OT papers developed AI tools without preferences of techniques. Only Cheng et al. (2020) used relatively large data with over 10,000 samples. Others had relatively small-sized data for developing algorithms (e.g., Yan et al., 2020) or showed unclear data information (e.g., Borup & Schütte, 2020).

4. Discussion

The review suggests that the field of AI-HRM is still in its infancy, despite its rapid growth in recent years. The field is rather fragmented, with studies from different disciplines covering a wide variety of topics. While CS and EO papers focused more on developing AI tools to facilitate HRM, ME and OT papers were more interested in general issues related to AI usage, particularly in topics related to AI-induced job loss or job changes. Our critical evaluation reveals that scholars need to pay attention to theoretical and methodological rigor. In terms of theories, all disciplines were rather weak in theoretical developments, indicating that the current field is perspective- and practice-oriented. The evaluation of methods identified data validity was the most notable methodological pitfall. We also call for a more rigorous and standardized approach for new AI methods. Based on the literature review, we discuss key issues, propose specific recommendations for future research, and elaborate on theoretical and managerial implications in the following.

4.1. *Critical summary and recommendations for future research*

Definition of AI. Our comprehensive literature review revealed a vague and sometimes inconsistent definition of AI. This is problematic because it might contribute to inaccurate assessments of AI's impact and/or insufficient interdisciplinary integration. The term AI was sometimes applied to technologies that were not AI, which Willcocks (2020) called "AI hijack." For example, Blanas et al. (2019) investigated AI-induced job loss brought about by "information and communication technologies, software, and especially industrial robots." However, this description could include almost anything related to computer applications, so the research could be exaggerating or even misunderstanding the influences of contemporary AI. Only 21% ($n = 39$) of papers had a clear definition of AI, mostly in ME domains ($n = 26$). Others took the term for granted and sometimes incited confusion. Scholars in various disciplines tended to describe AI differently, which reinforced the difficulties of interdisciplinary synthesis. The vagueness of the definition was particularly problematic for papers that focused on general outcomes or impacts of AI, as exemplified in Blanas et al. (2019). Table 5

Table 5
Summarized examples of variated AI terms.

	Example of terms	Example of sources
Narrow terms	bee colony optimization algorithm; ontology technology; sematic web; support vector machine; tabu search; fuzzy clustering	Delgado-Osuna et al., 2016; Geva et al., 2021;
Regular terms	neural network; learning algorithm; machine learning; speech recognition; text-mining; data mining; deep learning; machine learning; chatbot; expert system; intelligent technology; robotics	Acemoglu & Restrepo, 2020; Huang & Rust, 2018; Lambrecht & Tucker, 2019
Broad terms	internet of things; digitalization; Industry 4.0; automation; disruptive technologies	Autor, 2015; Blanas et al., 2019; Yuhong & Xiahai, 2020

provides a summary of different AI variations in prior research, classifying AI from broad to narrow terms and specific applications and providing examples of key terminology. Most broad terms are technologies related but not exclusive to AI, confirming the "AI hijack" (Willcocks, 2020). The mixture of AI with other concepts inhibits gaining an accurate understanding of AI's developments, implications, and impacts (Willcocks, 2020). Thus, future research needs to realize the boundaries of the concept when researching AI.

In response, we propose a unified definition of AI based on abductive reasoning of the extant literature, i.e., drawn from the synthesis of 39 inconsistent definitions. After careful observation, comparison, and syntheses of prior AI definitions, we argue that AI, despite variations, shares several key features, namely abilities for 1) learning, 2) interpreting environment, 3) autonomous operation, and 4) mimicking human cognitive ability/solving cognitive tasks (please see Appendix B for more details). Therefore, we define AI as artificial tools that can automatically accumulate experience (i.e., make sense of objective environments) and constantly learn from past experience to perform cognitive tasks. First, "artificial tools" include both material (e.g., robots) and nonmaterial (e.g., IT systems) artifacts, as AI in prior research referred to various types of artificial tools, including systems (e.g., Makarius et al., 2020), algorithms (e.g., Recht & Bryan, 2017), robots (e.g., Waytz & Norton, 2014), and more. Second, AI should have the ability to operate automatically with the least human intervention (e.g., Acemoglu & Restrepo, 2020). Third, AI should have the ability to accumulate experience through interpreting and interacting with environments or contexts, usually in the form of unstructured data (e.g., Dalenberg, 2018). Fourth, AI should have the ability to learn from experience (e.g., Prentice, Dominique Lopes, & Wang, 2019): learning is the key feature in differentiating AI from other autonomous technologies, such as personal computers. Last, AI should mimic human intelligence and thus be able to conduct cognitive tasks that are normally ascribed to humans, such as decision-making (e.g., Prüfer & Prüfer, 2020).

Topics in AI-HRM research. The literature review suggests a lack of interdisciplinary synthesis in the AI-HRM field, although there were some consistent foci and findings across different disciplines. The insufficient synthesis is particularly noticeable between the more technical disciplines (i.e., CS and EO) and the less technical disciplines (i.e., ME and OT). For example, while the more technical disciplines offered many AI tools for supporting HRM, the less technical disciplines paid limited attention to the effectiveness of the developed tools in real managerial contexts. We encourage future research to foster interdisciplinary integration by focusing on the following potential topics.

First, scholars can contribute to the interdisciplinary validation of AI tools. Many tools offer similar functions with different designs, i.e., different combinations of AI techniques and HR variables, but ignore rigorous validation. For example, although 27 papers from the CS, EO, and ME domains developed AI tools for HR staffing, there was limited discussion about the effectiveness, efficiency, and validation of these staffing tools from a managerial perspective. HR scholars will be particularly responsible for future managerial validation, considering the insufficient HRM knowledge in the technical fields. Moreover, although many tool developers conducted technical validations in their own papers, the lack of comparison between different tools suggested an invalidity of developed tools, even from the technical perspectives. A comprehensive and persuasive tool validity requires evidence from both technical and managerial evaluations and thus calls for interdisciplinary collaborations to deliver a series of studies. For instance, Suen, Hung, and Lin (2019) developed and technically validated a tool for AI interview rating, followed by managerial validations from Suen, Chen, and Lu (2019) and Suen et al. (2020), who, respectively, proved the perceived fairness and effectiveness of the tool. Their validity process across the disciplines of CS and psychology provided a valuable example for future scholars to follow.

Second, scholars can contribute to a more rigorous and inclusive discussion of AI-induced technological unemployment and the future of work. The CS and OT domains were more optimistic in topics concerning AI-related job loss compared with the ME domains. Interestingly, most of the pessimistic ME papers had conducted macro-level studies, while the more optimistic papers in CS and OT focused on meso- or micro-level analyses. This pattern suggests possible shortcomings in the current discussion of AI-human job relationships, namely, the exaggerated AI impacts, as macro-level studies could include effects that were not attributable to AI. While many scholars have argued the importance of social and political factors in AI diffusion (e.g., Fleming, 2019), it will be important to include micro-level insights into the integrated socio-technical influences in future studies of AI-job relationships. Furthermore, micro-level discussions of AI-induced unemployment were limited to specific contexts, particularly in the healthcare sector. We call for further research into other contexts to provide a more comprehensive picture.

Theories in AI-HRM research. The above review demonstrates a general trend of underdeveloped theoretical foundations in the AI-HRM field. Fewer than a quarter of the studies used solid theories to build their research, and many theoretical implications were rather superficial. The more technical disciplines, such as CS, usually contributed by responding to practical phenomena instead of developing theories. Nevertheless, we still identified a substantial portion of studies with weak theoretical foundations, even in the less-technical disciplines, indicating an urgent call for future theoretical applications and contributions. Therefore, we provide the following recommendations.

First, interdisciplinary collaboration can enhance the theoretical foundations in the more technical disciplines. Although practical-driven research may be a convention in technical disciplines, developers' insufficient HRM knowledge incurs significant shortcomings of AI tools (Cappelli, 2019). For example, Fan et al. (2012) relied on available data instead of HRM literature to determine their input variables during the development of turnover-prediction AI. However, the descriptive approach reduced the reliability and generalizability of the developed AI tool: the included variables could be incomplete, context-based, and even biased without theoretical justification. Management scholars can help technical disciplines reduce such ineffectiveness by offering more HRM theoretical insights. Furthermore, many management constructs are rather abstract, which reduces their potential to benefit technical developments. In responding to the issue, HRM scholars can further develop current constructs with visible proxies. For example, scholars can develop adaptive skill taxonomies to reduce the theoretical barriers in measuring AI impacts (Frank et al., 2019) or AI-based employee evaluations.

Second, scholars can empirically test and extend newly developed theories. Our review found four new theories: the professional task-automation framework (Sampson, 2021); the robot acceptance safety model (You et al., 2018); the theory of AI job replacement (Huang & Rust, 2018); and the decent work through automation model (Tuomi et al., 2020); as well as two new constructs: bounded automation (Fleming, 2019) and shadow learning (Beane, 2019b). The newly developed theories were specifically for AI-HRM research, so they have great potential to contribute to the field. However, new theories need further empirical evidence to become validated and established. Therefore, future research can help with the theory validation.

Here, we discuss the theory of AI job replacement as an example for future theoretical contributions. According to the theory (Huang & Rust, 2018), humans have mechanical, analytical, intuitive, and empathetic intelligence to perform different types of tasks in a given job position. AI replacement of humans will happen from mechanical to empathetic tasks due to the limited ability of AI, so it will take time for AI to replace an entire job. The theory provided a conceptual taxonomy of job tasks, which is highly relevant to the dynamic occupational boundary under the influences of advanced technologies. However, it has relatively vague constructs and insufficient empirical evidence. Therefore, we propose three potential paths to further develop the exampled theory. First, future scholars can consolidate the new constructs, either by validating new measurement scales or borrowing knowledge from previous studies. For instance, although Huang and Rust (2018) did not offer empirical details of empathetic intelligence to set a clear construct boundary, it is feasible to validate the scope of measurements based on previous knowledge due to the theoretical closeness between empathetic intelligence and some other established constructs (e.g., emotional intelligence).Second, scholars can increase the theoretical reliability and usefulness by crafting the details of the theory. For example, the current conceptual taxonomy of job tasks is rather simple, which limits the potential to use the theory in different empirical contexts. It would benefit the AI-HRM field if future research developed a more comprehensive taxonomy.Third, we call for empirical validation of the proposed theoretical relationships and assumptions. While the original theory argues that current AI is replacing analytical and intuitive tasks, future studies may help distinguish the different speeds and patterns of replacement by offering thorough investigations and explanations of how AI replacement happens and what factors are relevant. Instead of simple empirical tests of the theory, such studies could significantly extend the boundary and enhance the underlying logic thereof.

Third, scholars can help with the synthesis of existing theories. Table 6 shows the most popular theories in prior research. We found CASA theory and socio-technical systems theory particularly promising (Makarius et al., 2020; Ötting & Maier, 2018). CASA suggests that humans perceive technology as social actors, the same as they do with other humans. Socio-technical systems theory focuses on the joint optimization of organizational technical and social systems, arguing that interactions between technical-social systems have effects on the outcomes of technology. Because of their emphases on the social aspects of technology, we propose that the two theories, which are from different disciplines, can help HRM scholars gain a better understanding of AI through managerial and social lenses. Both theories are rather broad, which leads to notable theoretical gaps and high potential for future theoretical synthesis. Scholars can extend these theories by integrating them with other established management theories. For example, socio-technical systems theory is particularly well suited for AI implementation issues. Makarius et al. (2020) provided an example of theoretical synthesis with an organizational socialization framework in AI-employee integration research. Here, we further propose two compatible theories with high potential for future theoretical integration. First, technology diffusion theories in the information systems field are promising for extending socio-technical systems theory. While the theory emphasizes social-technical systems, it remains unclear what constitutes these systems. Several established technology diffusion theories can offer a theoretical lens into the components of social-technical systems. For example, the technology-organization-environment (TOE) model of technology diffusion includes comprehensive

Table 6
Most popular theories in prior research.

Name of theory	Category	Authors	Journal	Topic
Big five	CS	Köchling et al. (2021)	*Business & Information Systems Engineering*	Evaluated fairness of AI in interviews
	CS	Faliagka et al. (2014)	*Artificial Intelligence Review*	Developed an AI to evaluate candidates
	CS	Suen, Hung, and Lin (2019)	*IEEE Access*	Developed an AI-based interview tool
	CS	Suen et al. (2020)	*Human-Centric Computing and Information Sciences*	Evaluated the effectiveness of AI interview raters
	ME	Spisak et al. (2019)	*The Leadership Quarterly*	Promoted AI method in management research
	ME	Minbashian et al. (2010)	*Organizational Research Methods*	Promoted AI method in management research
Organizational justice theory	CS	Robert et al. (2020)	*Human-Computer Interaction*	Proposed a design agenda fair AI
	ME	Newman et al. (2020)	*Organizational Behavior and Human Decision Processes*	Evaluated perceived fairness of AI
	OT	Ötting & Maier, (2018)	*Computers in Human Behavior*	Evaluated perceived fairness of AI
Social information processing theory	CS	Suen, Hung, and Lin (2019)	see above	see above
	OT	Suen, Chen, and Lu (2019)	*Computers in Human Behavior*	Evaluated candidates' perceptions toward AI
Computers-are-social-actors theory	OT	Lee (2018)	*Big Data & Society*	Evaluated perceived fairness of AI
	OT	Ötting & Maier, (2018)	see above	see above
Socio-technical systems theory	ME	Wall et al. (1992)	*Journal of Applied Psychology*	Evaluated HRM impacts on AI performance
	ME	Makarius et al. (2020)	*Journal of Business Research*	Proposed an AI-employee integration model

variables from different technological, organizational, and environmental systems that influence AI implementation (Pan, Froese, Liu, Hu, & Ye, 2021). By integrating the TOE model, future scholars can increase the validity and reliability of social-technical systems theory. It may also be compatible with the information system success model of predicting the success of new technology (e.g., Nguyen & Malik, 2021) by helping identify the influential socio-technical factors of AI success.

Furthermore, psychological theories in human interaction seem to fit well with social-technical systems theory, given the demonstrated interactions between social-technical systems and the assimilation of human-computer relationships. In particular, we propose social exchange theory as a candidate for potential theoretical synthesis. Social exchange theory argues that social interactions between individuals lead to social or economic outcomes for each party via reciprocity norms. When AI replaces one of the parties or mediates the exchange, social-technical systems theory overlaps with social exchange theory. Prior research has already discussed the influences and outcomes of AI-mediated social interactions based on social exchange theory (e.g., Malik et al., 2020; Malik et al., 2021). While social exchange perspectives emphasize social outcomes, and social-technical systems theory puts more focus on technical outcomes, an integrated framework of both theoretical lenses may provide a more comprehensive picture of how AI and employees interactively influence organizational outcomes.

Methods in AI-HRM research. Our literature review revealed that while papers from different disciplines suffered from different methodological shortcomings, they shared the problem of data quality. First, the measurement validity was often insufficient for survey data in all disciplines, including some ME papers. Second, the data quality justification was often insufficient for secondary data, particularly in EO and ME papers. To address the methodological limitations, we provide the following recommendations for future research.

First, we encourage future research to increase data validity. For secondary data, transparent information can easily increase and justify data quality. For survey data, the quality depends on the quality of a survey's design, and validity procedures help justify the quality. A good quality survey starts from measurements with theoretical justifications. Furthermore, to capture individual perceptions, it is better to use measurement scales for constructs instead of using single items (Collado-Mesa et al., 2018). To validate the scales used, scholars need to check a series of measurement validities, e.g., convergent validity and discriminant validity. For cross-sectional data, extra effort is required to control and eliminate common method variances. Although the above process may be familiar to many HRM scholars, the review indicated that scholars in other disciplines had insufficient methodological knowledge of survey research. We believe that interdisciplinary collaborations could benefit the overall AI-HRM field.

Second, we encourage future scholars to learn from papers that promote AI methods. The problem of data validity demonstrated the difficulty of collecting high-quality data in AI-HRM studies. AI techniques perform better than traditional statistical techniques in data analysis, particularly for complex data (De Oliveira et al., 2013); thus, they allow scholars to take advantage of data from unconventional sources (e.g., Prüfer & Prüfer, 2020). Therefore, they have great potential in facilitating future HRM studies by reducing data limitations. Compared with more traditional methods, AI methods are difficult for HRM scholars due to a lack of know-how about integrating AI methods and the technical incapability to understand the techniques. Although papers adopted different standards, they still provided insights into the "know-how" to help future scholars use the AI method. We synthesize these insights and encourage future scholars to consider the following approach.

Our proposed approach aims to provide basic and general guidance for using the AI method instead of providing fixed rules. Above all, the tieback with theory and process transparency are the two fundamental principles in using the AI method (e.g., Choudhury et al., 2021; Somers & Casal, 2009). The first step in using the AI method is the justification of the chosen technique(s) by explaining linkages between technical characteristics and research purpose. For example, a neural network fits well with exploratory studies due to its strong ability in pattern recognition from unstructured data; however, it is not suitable for causal test studies because the results from a neural network include no linear relationships (Somers & Casal, 2009). The second step is data preparation, which includes variable selection deriving from theories, data processing, and data partition for training and validating the AI (e.g., Choudhury et al., 2021). The third step includes model building and validating by using multiple-fold cross-validation (e.g., Campion et al., 2019), checking measurement validity if applicable (e.g., Speer, 2020), and comparing with traditional methods (e.g., Abubakar et al., 2019). The last step is the correct interpretation of results based on theoretical knowledge (Choudhury et al., 2021).

4.2. *Implications for research*

Our review makes several contributions to HRM research. First, we provide an interdisciplinary overview of AI-HRM research. For the AI-HRM field, prior research has suffered from insufficient reflection due to a lack of interdisciplinary synthesis. As Seeber et al. (2020) commented, "We do not know what we do not know." Our review contributes to the field by synthesizing fragmented interdisciplinary literature from the perspectives of topic, theory, and method. We further provide suggestions to scholars in responding to the extant literature's shortcomings. For example, we identify literature gaps and propose specific topics that deserve further research attention. In addition, we propose an interdisciplinary definition of AI to integrate disconnected areas. The proposed definition can help scholars to realize and identify boundaries of existing and future research in different contexts; thus, our efforts will benefit future scholars and practitioners in understanding the topic's boundaries, delivering high-quality research, and facilitating AI implementation in industry.

Second, we contribute to the literature by critically evaluating the theoretical foundations of the extant literature and outlining directions for future research. Our review reveals that most prior studies were relatively weak in theoretical developments, regardless of discipline. Only 21% of the papers used theories (see Appendix), and many of these used theories rather superficially (e.g., Faliagka et al., 2014). To increase the impact and generalizability of research, it is important to have a theoretical foundation. We outline three strategies for integrating theory into AI-HRM research. First, scholars in management disciplines could cooperate with technical scholars and produce theoretical constructs or frameworks that fit the needs of technical design, so the overall AI-HRM community can benefit from generalizable theories.

Second, researchers may build theories specifically for AI-HRM research by extending and empirically testing new theories. We introduced four new theories (e.g., Sampson, 2021) and two new constructs (e.g., Fleming, 2019) in our reviewed papers, and used the theory from Huang and Rust (2018) as an example to show the potential of future theoretical contributions. Finally, scholars can adjust existing theories to AI-HRM research. We identified the five most popular theories (see Table 6) and proposed two other popular theories with high potential for theoretical development (e.g., Lee, 2018; Makarius et al., 2020).

Third, we contribute to a better understanding of methodological rigor with a critical evaluation of methods in prior literature. We offer suggestions for future research to avoid common pitfalls and hopefully motivate future (management) scholars to apply AI research methods. Our evaluation suggests that data validity remains problematic in AI-HRM research. We also propose strategies to increase methodological rigor by increasing measurement validity and introducing AI methodology. We further propose and explain a general approach for implementing AI methods in future management studies based on prior AI method papers (e.g., Choudhury et al., 2021; Minbashian et al., 2010).

4.3. Implications for practice

The research has several practical implications. First, we provide quick access for IT developers, HR practitioners, and managers to easily gain knowledge related to their interests within the broad topic of AI-HRM. The fragmented literature and fuzzy definition of AI set a relatively high entry barrier for nonexperts to acquire AI-HRM knowledge. Since our review covers a wide variety of studies and summarizes main topics in the field, readers in the industry can rely on our paper to draw a comprehensive picture of current trends and make strategic decisions based thereon.

Second, we recommend that investors exercise caution when deciding to invest human and monetary capital in a new AI project. Considering the imbalanced topics of AI tool development and tool validation, many developed AI tools may not be effective or useful. The possible low industrialization of developed AI may indicate a low return of investments, at least in the short term. Therefore, for companies wanting to purchase AI tools for HRM, it may be smart to only invest in relatively mature tools, such as recruitment AI, which already had validations from academia. Alternatively, companies could jointly develop AI tools, ideally in cooperation with AI and HRM experts.

Third, AI developers need to revisit the design of current AI tools that lack the support of management knowledge. The practical-oriented design of AI tools may be ineffective or even introduce problems to HRM when developers have insufficient HRM knowledge. Consequently, the current design of AI may reduce organizations' desires to use AI, which in turn limits the long-term technical development of AI technology due to a lack of industrialization and investments, although AI has great potential to shape HRM and the future of work.

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Author statement

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Fabian Jintae Froese is the second and corresponding author of the manuscript. He was responsible for supervison, and helped with conceptualization, methodology, reviewing, revising and editing the manuscript.

Appendix A. Theories and theoretical constructs in prior research

	Source	Study Nature	HRM functions	Theory
CS	Abubakar et al., 2019	Empirical	General	Psychological ownership theory, social exchange theory
	Faliagka et al., 2014	Empirical	Recruitment	Big five (used only one dimension)
	Jayaratne & Jayatilleke, 2020	Empirical	Recruitment	HEXACO, i.e., a personality model similar to big five with six factors
	Khosla et al., 2009	Empirical	Recruitment	Maslow's model of needs, selling behavioral model
	Köchling et al., 2021	Empirical	Recruitment	Big five
	Lee & Ahn, 2020	Empirical	Recruitment	Myers-Briggs-type-indicator (MBTI), i.e., a personality model with 16 types of personalities

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	Source	Study Nature	HRM functions	Theory
	Lukovac et al., 2017	Empirical	Performance	BCG matrix
	Robert et al., 2020	Conceptual	General	Organizational justice theory
	Suen, Hung, & Lin, 2019	Empirical	Recruitment	Social information processing theory, big five
	Suen et al., 2020	Empirical	Recruitment	Social signaling theory, big five
EO	Chaturvedi et al., 2005	Conceptual	Recruitment	First generation labor supply model
	Kontogiannis & Kossiavelou, 1999	Conceptual	Employee well-being	Tactical decision making under stress (TADMUS) model
	You et al., 2018	Empirical	Employee well-being	(Self-developed) Robot Acceptance Safety Model (RASM)
ME	Barrett et al., 2012	Empirical	General	(Generic construct) Pickering's concept of tuning
	Beane, 2019b	Empirical	Training	(Self-developed) “shadow learning” construct
	Choudhury et al., 2020	Empirical	Performance	(Generic construct) decision-making framework, human capital constructs
	Dekker et al., 2017	Empirical	General	(Generic construct) economic self-interests construct
	Fleming, 2019	Conceptual	General	(Self-developed) “bounded automation” construct
	Gu et al., 2019	Empirical	Performance	Performance maintenance theory of leadership, media synchronicity theory
	Holford, 2022	Conceptual	General	(Generic construct) constructs of authority and control
	Huang & Rust, 2018	Conceptual	General	(Self-developed) theory of AI job replacement
	Lawler & Elliot, 1996	Empirical	Performance	Behavior decision theory
	Liu et al., 2020	Empirical	Turnover	(Generic construct) resource-based view constructs
	Makarius et al., 2020	Conceptual	General	Socio-technical systems theory, organizational socialization framework
	Minbashian et al., 2010	Empirical	Performance	Big five
	Newlands, 2020	Conceptual	Performance	Henri Lefebvre's spatial triad theory
	Newman et al., 2020	Empirical	Performance	Organizational justice theory
	Roth & Peranson, 1999	Empirical	Staffing	(Generic construct) game theory: two-side matching concept
	Sampson, 2021	Empirical	General	(Self-developed) professional task-automation framework
	Spisak et al., 2019	Empirical	Performance	Big five
	Wall et al., 1992	Empirical	Performance	Socio-technical systems theory
	Xu et al., 2020	Empirical	General	Organizational change theory
OT	Jackson et al., 2020	Empirical	General	Social categorization theory
	Lee, 2018	Empirical	General	Computers-are-social-actors theory (CASA)
	Linden, 2017	Empirical	General	Social construction of technology
	Ötting & Maier, 2018	Empirical	General	Computers-are-social-actors theory (CASA), organizational justice theory
	Randell et al., 2021	Empirical	Performance	Negotiated order and boundary theory
	Suen, Chen, & Lu, 2019	Empirical	Recruitment	Social information processing theory, media richness theory, social interface theory
	Tuomi et al., 2020	Empirical	General	(Self-developed) decent work through automation model

Appendix B. Prior definitions of AI and its variations

Source	AI (and its variations)refers to…	Defined feature
Acemoglu & Restrepo, 2020	Industrial robot, which is an automatically controlled, reprogrammable, and multipurpose machine.	Autonomous operation
Acemoglu & Restrepo, 2020b	Intelligent machines or agents, which are machines, softwares or algorithms that act intelligently by recognizing and responding to their environment.	Interpreting environment
Barrett et al., 2012	An automatic device that performs functions normally ascribed to humans or a machine in the form of a human.	Autonomous operation, Cognitive ability
Benders, 1995	Industrial robot, which is an automatically controlled, reprogrammable, multi-purpose, manipulative machine with several degrees of freedom.	Autonomous operation
Berg et al., 2018	Robot, which is a combination of computers, artificial intelligence, big data and the digitalization of information, networks, sensors and servos that are emphasized in the literature on the new machine age	
Bromuri et al., 2021	AI-based machine learning, which aims at exploiting data to create a model of a process that a human cannot characterize otherwise and has the ability to learn to interpret human behavior.	Learning, Interpreting environment
Cheng et al., 2020	A general term that implies the use of computers to model intelligent behavior with minimal human intervention.	Autonomous operation, Cognitive ability
Choudhury et al., 2020	The capability of a machine to imitate intelligent behavior, in its current technological state takes the form of machine learning, where computers improve their learning over time autonomously, through programs which utilize additional observational data and information from real-world interactions	Learning, Interpreting environment, Autonomous operation, Cognitive ability
Dalenberg, 2018	Any device that perceives its environment and takes actions that maximize its chance of success at some goal. It learns how to make decisions by machine learning techniques.	Learning, Interpreting environment
Dekker et al., 2017	Robots, machines that can navigate through and interact with the physical world, especially the advanced robot with the application of machine-learning algorithms	Learning, Interpreting environment

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Source	AI (and its variations)refers to…	Defined feature
	that do not require tasks to follow a well-defined protocol, and the "cobots" which are robots designed to interact with humans.	
Fleming, 2019	Highly advanced computer algorithms, which not only mimic human capabilities (e.g., opening a door), but display a sort of person-like reflectivity while doing so (e.g., judging when and how the door should be opened in a polite manner).	Cognitive ability
Gruetzemacher, Paradice, & Lee, 2020	Powerful, general AI systems which can be thought of as cognitively equivalent to humans.	Cognitive ability
Hammershøj, 2019	AI has shifted focus from rule-based systems, in which rules are programmed directly, to statistical pattern recognition systems, in which the machine learns the patterns from data sets. The latter form of AI is a more complex kind of machine learning capable of making predictions on its own.	Learning, Autonomous operation
Huang et al., 2019	Technologies that mimic (or even surpass) human intelligence.	Cognitive ability
Jung & Lim, 2020	Industrial robot, which is automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes for the use in industrial automation applications.	Autonomous operation
Kontogiannis & Kossiavelou, 1999	"Narrow AI" that equals or exceeds human intelligence with regards to specific tasks, specifically including 1) a range of knowledge-based systems or software agents; 2) smart construction objects, i.e., construction resources (e.g., machinery, tools, etc.) that are made smart by augmenting them with sensing, processing, and communication abilities, so that they have autonomy and awareness, and can interact with the vicinity to enable better decision making.	Interpreting environment, Autonomous operation, Cognitive ability
Lawler & Elliot, 1996	Expert system, i.e., a computer program which attempts to embody the knowledge and decision-making facilities of a human expert in order to carry out a task requiring human expertise. It replicates certain abstract reasoning and problem-solving capabilities of humans.	Cognitive ability
Lee, 2018	A computational formula that autonomously makes decisions based on statistical models or decision rules without explicit human intervention.	Autonomous operation, Cognitive ability
Li et al., 2019	The simulation of human intelligence processes that allows computer systems to automatically learn from experience and perform human-like tasks to improve efficiency of daily task.	Learning, Autonomous operation, Cognitive ability
Lingmont & Alexiou, 2020	Automation, the technology by which a process or procedure is performed with minimum human assistance	Autonomous operation
Makarius et al., 2020	A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation, such systems should sense, comprehend, act, and learn, mimicking a person applying intelligence.	Learning, Interpreting environment, Cognitive ability
Oh et al., 2019	The ability of computer systems to perform tasks that would usually require human levels of intelligence.	Cognitive ability
Pettersen, 2019	Computer systems that perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision making or translation.	Cognitive ability
Prentice et al., 2019	A system's ability to correctly interpret external data, to learn from such data and use those learnings to achieve specific goals and tasks through flexible adaptation, including six dimensions: autonomy, ability to learn, reactivity, ability to cooperate, humanlike interaction, and personality.	Learning, Interpreting environment, Autonomous operation
Prüfer & Prüfer, 2020	A broad concept, in which algorithms and machines mimic cognitive functions of learning and problem solving, so they are able to adapt to different situations and to carry out tasks in a way that we would consider smart or intelligent.	Learning, Cognitive ability
Recht & Bryan, 2017	Machine learning, which implies algorithms that can learn from and make predictions on the basis of new data. A computer program is said to learn from experience E with respect to some class of tasks T and performance P if its performance at tasks T, as measured by P, improves with experience E.	Learning, Interpreting environment
Robert et al., 2020	Computer systems that can sense, reason, and respond to their environment in real time, often with human-like intelligence.	Interpreting environment, Cognitive ability
Sampson, 2021	Automation, with which information and decision tasks are partially or completely performed by computers, reducing the need for human effort.	Autonomous operation
Seeber et al., 2020	The capability of a machine or computer to imitate intelligent human behavior or thought. Though how this machine should behave or think is disputed: a affective AI learns to incorporate and understand emotional signals from humans, but a rational AI would always base its decision-making on optimizing its objectives, rather than incorporating social or emotional factors. AI research has not yet produced technology capable of critical thinking and problem solving on par with human abilities, but progress is being made toward those goals.	Learning, Interpreting environment, Cognitive ability
Somers & Casal, 2009	Artificial Neural Networks, which are pattern-recognition algorithms that capture salient features from a set of inputs and map them to outputs.	
Spisak et al., 2019	Machine learning, which is an automated computational process for "learning" patterns in data from repeated experience to improve performance on tasks such as prediction.	Learning, Interpreting environment, Autonomous operation
Suen, Hung, & Lin, 2019	A branch of computer science that seeks to produce intelligent machines that respond in a manner similar to human intelligence. It aims to extend and augment human	Learning, Cognitive ability

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Source	AI (and its variations)refers to…	Defined feature
	capacity and efficiency of mankind in tasks of remaking nature, with machine learning as a major approach for achieving AI.	
Suen, Chen, & Lu, 2019	Intelligent systems that act and reason as humans in a specific domain.	Cognitive ability
Suen et al., 2020	A branch of computer science that seeks a new type of intelligent machine similar to human intelligence.	Cognitive ability
Tambe et al., 2019	A broad class of technologies that allow a computer to perform tasks that normally require human cognition, including decision-making.	Cognitive ability
Van Esch et al., 2019	Any intelligent agent (e.g., device) that distinguishes between different environments and can take a course of action(s) to increase the success of achieving predetermined objectives.	Interpreting environment
Waytz & Norton, 2014	Robot, an intelligent artificial being, typically made of metal and resembling in some way a human or other animal.	
Willcocks, 2020	(Technology) which seeks to make computers do the sorts of things minds can do. Today the term AI is often used when a machine mimics cognitive and other functions that humans associate with human minds, for example, learning, problem solving, visioning, prediction and association.	Learning, Cognitive ability
Xu et al., 2020	Service robots, which have the ability to perform the intended meaningful tasks depending on current state and sensing, without human interventions.	Interpreting environment, Autonomous operation

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