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HARNESSING AI IN HUMAN RESOURCE MANAGEMENT: A SYSTEMATIC ANALYSIS OF CURRENT RESEARCH AND PRACTICES

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Abstract : *The surging trends of ever-emerging technologies, especially Artificial Intelligence, seem to be revolutionizing every aspect of functioning in the world, including Human Resource Management (HRM). Various disciplines have tackled the intersection of AI and HRM including Management, Economics, Computer Science, Psychology, Medical Sciences, and others. Hence, in this paper I present results of a systematic interdisciplinary review of 150 articles. I synthesized prior research into four groups by branches of the discipline: management and economics, computer science, and psychology and medical sciences.*

In comparison to other disciplines, the studies which were focused on basic science and engineering practiced softer approaches and inclusive approaches to research objectives. Strength components from both psychology and medicine yielded results that there were gaps to be profound within social HRM such as AI applications within organizations between employers and employees. Within all categories, the underlying frameworks were lacking robust theoretical foundations. I therefore suggest such multi-disciplinary approaches to be developed, offer a single working AI definition for effective research and application, and discuss their consequences on professional conduct.

1. INTRODUCTION

Artificial intelligence (AI) is arguably one of the most transformative technologies redefining the modern labor market (e.g., Huang & Rust, 2018). While AI promises to enhance work by upgrading or complementing jobs (Autor, 2015), it also promises to pose enormous risks, such as potentially eliminating over 45% of jobs (Berg, Buffie, & Zanna, 2018) and increasing social inequality (e.g., Levy, 2018). Due to its extensive implications, AI can have a significant influence on the future of human resource management (HRM). The integration of AI in HR practices or so-called AI-HRM has prospects and challenges too (Malik, Budhwar, Patel, & Srikanth, 2020; Malik, De Silva, Budhwar, & Srikanth, 2021).

AI-HRM is cross-disciplinary in nature. Technological development depends on the emergence of computer science and other advancements but understanding their application as well as comprehending their implications is largely anchored in social science knowledge. Interdisciplinary researchers across various fields have contributed to knowledge in AI-HRM. For instance, computer scientists have created algorithms tailored to HR functions (Anandarajan, 2002), economists have explored AI's broader impact on labor markets (Berg et al., 2018), psychologists have examined how AI affects recruitment and employee behavior (Van Esch, Black, & Ferolie, 2019; Brougham & Haar, 2020), and medical researchers have highlighted that healthcare workers may be unprepared for AI adoption (Abdullah & Fakieh, 2020).

While research across all these fields is growing, few studies tackle AI-HRM from a narrow disciplinary angle, with little effort to interconnect knowledge across fields. Such syntheses are an opportunity missed because interdisciplinary work is crucial for the successful implementation of AI (Fountaine, McCarthy, & Saleh, 2019) and for the building of talent in the AI workplace (Pejic-Bach, Bertoncel, Meško, & Krstić, 2020).

To bridge this gap, this paper offers a systematic large-scale cross-disciplinary review of HRM and AI. My review has three important contributions. Firstly, it provides a comprehensive overview of the existing literature and describes the consolidation of findings across various disciplines to identify directions for future research. Second, it scrutinizes the theoretical foundations on which current AI-HRM research is built and dictates directions towards theory building—most importantly in fields like healthcare and computer science, where theoretical engagement is generally in short supply. Third, the study measures the methodological practices utilized across domains and offers examples of state-of-the-art AI approaches that could advance future management research. By highlighting the significance of cross-disciplinary methods such as the application of computer science techniques to management research I aim to encourage innovative, rigorous research in this rapidly evolving field.

2. NEED OF THE STUDY.

This research seeks to review systematically the existing academic literature regarding the use of AI in HRM, identifying themes and key issues, trends, challenges, and gaps in research. Through the synthesis of results, the review seeks to provide meaningful insights for researchers, HR professionals, and policymakers who seek to utilize AI without compromising ethical and quality human resource management practices.).

3.. RESEARCH METHODOLOGY

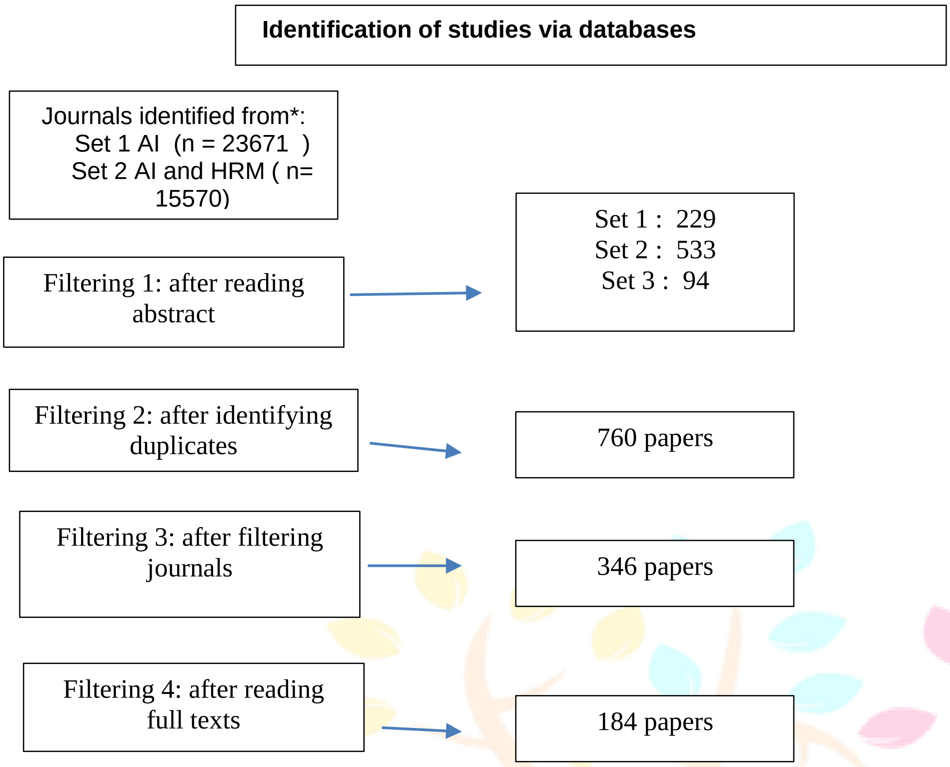
There is no clear definition of "artificial intelligence," as it can be used to mean various concepts (Willcocks, 2020). Although no one definition has been provided in existing literature, I had decided on a general context of AI for my study before I began my literature review. I was thinking of contemporary AI, guided by two fundamental principles. First, "contemporary" AI refers to sophisticated, intelligent systems with the capability of processing large-scale calculations and solving complex real-world issues (e.g., Nilsson, 2010). Consistently, we disregarded studies of less advanced AI, like personal computers. Second, I included only AI-specific studies, without studies on overall technological advancements, like technological disruption and Industry 4.0. These assumptions dictated my search and selection of relevant literature. Fig. 1 illustrates my search process.

3.1Population and Sample

I used systematic review techniques (Tranfield, Denyer, & Smart, 2003) that ensured extensive coverage and greater research reliability. I downloaded 41,831 articles from the Social Sciences Citation Index and Sciences Citation Index databases using Web of Science (WOS), which are two of the most extensive and widely used sources of peer-reviewed journal articles. Because the definition of AI was not well defined, it was challenging to create an exhaustive interdisciplinary collection using a single search. In an attempt to enhance inclusivity, I conducted three individual searches with different constraints, generating three distinct sets of literature. My search was for English-language reviews and articles between 2010 and 2024, including early access articles. I selected this time frame since contemporary AI came along with developments in computer hardware, something that was only achievable after the early 2010s using supercomputers with thousands of processors (for example, Haenlein & Kaplan, 2019). In my initial literature searching round, I put few restrictions and used the basic search term "artificial intelligence" across all journals and domains. This yielded 23,761 articles. In my second round, I became more specific in my search by using more descriptive parameters, such as both AI and HRM. In specifying search terms concerning AI, I borrowed those used in a systematic review of AI in healthcare (Senders et al., 2018).

3.2 Data and Sources of Data

Fig. 1. Process of literature search and selection



I performed a single slight modification to AI-specific search terms by including "robot*," in accordance with conventions in AI-HRM research (e.g., Berg et al., 2018). For HRM parameters, I borrowed and synthesized terms from two interdisciplinary systematic reviews of HRM literature (Garcia-Arroyo & Osca, 2019; Voegtlin & Greenwood, 2016). Furthermore, I performed two slight adjustments: (1) excluding "work" to prevent overgeneralization and (2) including "labor, labour, job*," in line with AI-HRM literature conventions (e.g., Acemoglu & Restrepo, 2020). Employing these specific search terms for all journals and fields, I retrieved a combined total 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*).*

In the third iteration of my literature search, I imposed more constraints by filtering to Financial Times (FT) 50 journals, which are high-quality journals for management papers. Because AI is frequently spoken about in wide terms by scholars of management,I broadened my search criteria for AI using the addition "algorithm*" to increase inclusiveness of the literature. Nevertheless, I left out such terms as "automation" and "digitalization," since they are too broad to be able to meaningfully differentiate AI from other info-techs. Employing the same HRM keywords and the slightly longer AI keywords, I searched FT50 journals and received a total of 2,500 papers.

3.3 Selecting literature

In the process of selecting the literature, I employed the technique of "presumption of inclusiveness." In this, if an article used generic terms (e.g., "digitalization") and it was unclear whether they entailed AI or not, we preferred to include it. This helped in minimizing selection complexity because of vagueness around the term AI. I applied a four-step filtering technique to the literature.

1. Abstract Screening: I screened the abstracts of all 41,831 papers and filtered out those that were clearly not related to HRM or AI, leaving us with 856 papers.
2. Duplicate Removal: I filtered out duplicate entries, leaving us with 760 papers.
3. Filtering of Journal Quality: I excluded articles published in FT50 and Web of Science (WOS) Quarter 1, reducing the number to 346 articles. For inter-disciplinary journals with multiple rankings in varying disciplines, I employed two rules for prioritization:

Disciplinary Hierarchy: Subject relevance was used to prioritize journals, with management being the first priority, computer science (CS) being the second, followed by healthcare, psychology, and other disciplines (i.e., management > CS > healthcare > psychology > others).Management was prioritized at the top since my primary area of research was management, followed by CS since AI is technical in nature. Healthcare and psychology were ranked as superordinate categories since they have more than one subdiscipline (e.g., educational psychology, developmental psychology). Ranking between healthcare and psychology was determined by convenience rather than by content overlap.

Field Dominance: Journals in the "others" category ranked based on the most common journal discipline, favoring the fields with the most powerful impact.

4.full-Text Review: I read thoroughly the complete texts of the remaining 346 papers, rejecting further those that were not AI or HRM related. This final step gave us a set of 150 papers. At full-text review, I rejected primarily three types of papers:

AI research in other fields of management, particularly corporate strategy.AI research into shop scheduling on manufacturing floor shop because it was closer to production rather than HRM, although loosely connected to staffing of employees.HRM research was into other technologies (i.e., cellular phones) without AI capability.The other 150 papers formed the basis of this review. Papers were drawn from 93 journals, representing 18 WOS disciplines (see Table 1). Table 2 lists all journals that have published three or more papers addressing AI-HRM.

3.4. Analysing literature

I categorized papers into three sets of categories based on three deductive criteria. The first criterion was discipline. I categorized papers in 18 disciplines into four categories based on disciplinary closeness and the number of papers in each discipline. Thus, I could still indicate the disciplinary variations while simplified the complexity of finding presentations. The CS (computer science) discipline was big enough to be an independent category. I merged engineering with operation fields to develop the EO (engineering & operation) category and merged management with economics fields to develop the ME (management & economic) category. Other fields comprised the OT (other) category, where 43% (n = 15) of papers were in the healthcare

Table 1

Number of papers in different disciplines.

No.	Discipline	Number of Papers
1	Management	38
2	Computer Science	40
3	Economics	15
4	Healthcare	15
5	Operations	14
6	Engineering	8
7	Psychology	5
8	Social Science, Interdisciplinary	3
9	Law	2
10	Social Issue	—
11	Area Study	1
12	Communication	1
13	Environmental Studies	1
14	Hospitality	1
15	Multidisciplinary Sciences	1

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

Rank	Journal	Number of Papers
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

The first criterion for classification was study discipline. As indicated in Figure 2, the disciplines differed with Management and Economics (ME) having the highest percentage of studies, followed by Computer Science (CS), Other Technologies (OT), and Engineering and Operations (EO).

The second was according to the nature of studies, whereby empirical and conceptual papers were separated. The empirical category comprised work that utilized actual data from the actual world or tested models and algorithms in actual applied situations. The conceptual category comprised work that utilized no empirical data or only mock or simulated data, which I did not categorize as being in real-world environments. Figure 3 indicates that the majority of papers were empirical, with Computer Science having the highest proportion of empirical studies (85%, n = 41), followed by Engineering and Operations with the lowest proportion (64%, n = 16).

The final classification was based on the Human Resource Management (HRM) function addressed in each paper. Through standard HRM activities, I then established the following six primary functions: recruitment, performance and commitment, training, staffing, turnover, and staff well-being. Additionally, publications addressing more general HRM concerns unrelated to a specific function—unemployment or ethical HRM policy, for example—were assigned to a "general" category. This helped facilitate an integrated analysis of thematic focus across selected literature.

4. RESULTS AND DISCUSSION

Fig. 4 illustrates the publishing trend in AI-HRM research field from the year 2010 to 2024. There was a low level of research activity prior to 2016. However, there was an impressive burst of publications subsequently. This spurt appears dominated largely by research scholars from comparatively less technical backgrounds, viz., Management and Economics (ME) and Other Technologies (OT) which have documented a spectacular rate of increase of output since the year 2017.

In contrast, researchers belonging to more technical disciplines—viz., Computer Science (CS) and Engineering and Operations (EO)—have evidenced relatively less activity in terms of AI-HRM research areas. The slow pace of paper development in the EO discipline, particularly, indicates a relative lack of interest among engineering scholars.

This shift in research trend corresponds to a defining moment in public sentiment toward AI: the 2016 world champion Lee Sedol defeat at the hands of Google's AlphaGo, bringing widespread awareness of the power of contemporary AI technology. This was the most probable catalyst for greater interest in AI among non-specialist academic audiences, spurring the development of AI-HRM research.

With these inclinations, I anticipate continued and accelerating development of this interdisciplinary. The following subsections present thematic focus of literature and offer critical assessment of research available to us from a theoretical as well as methodological perspective.

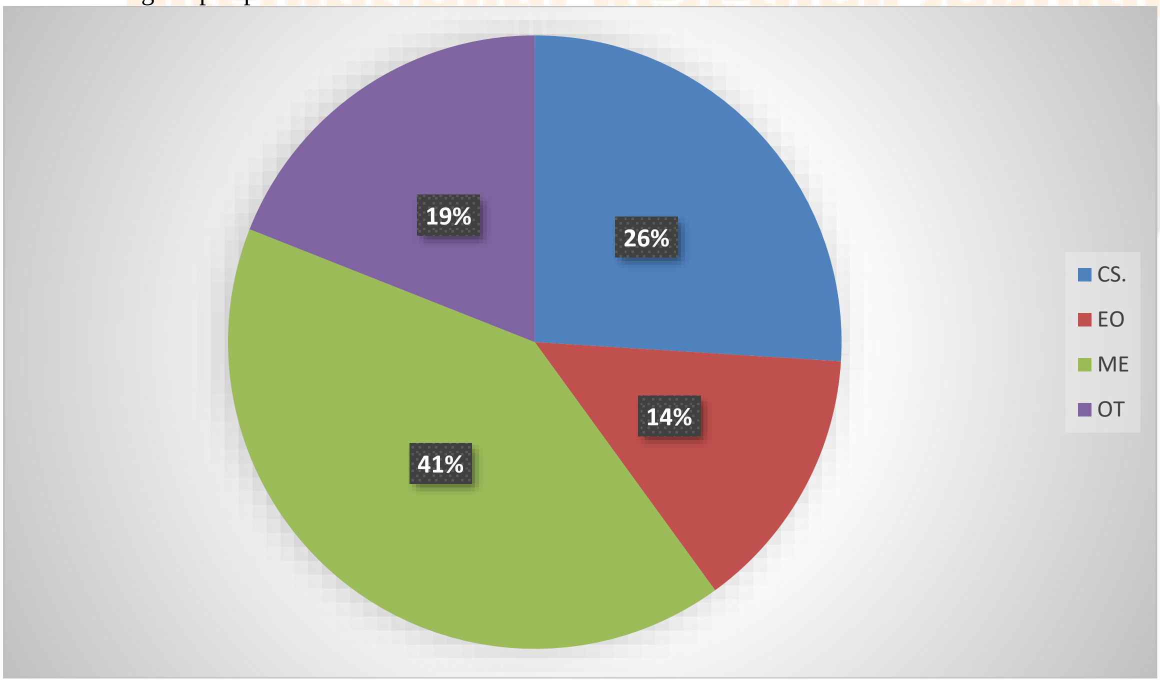


Fig. 2. Pie charts of disciplinary categories.

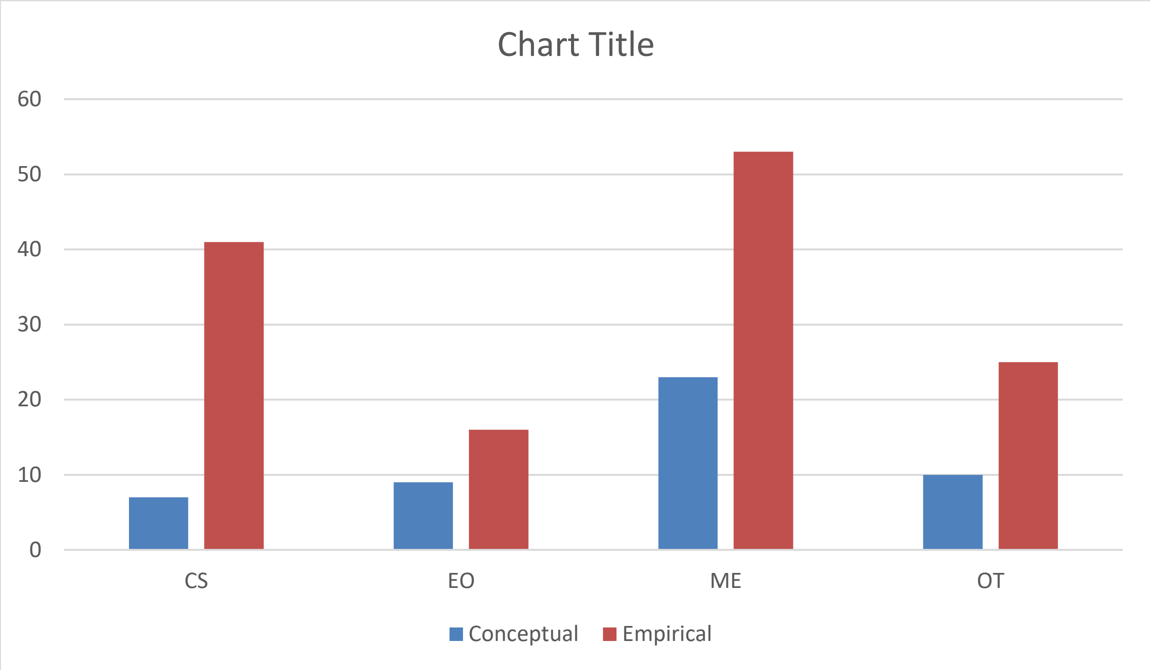


Fig. 3. Numbers of conceptual and empirical papers by disciplinary categories.

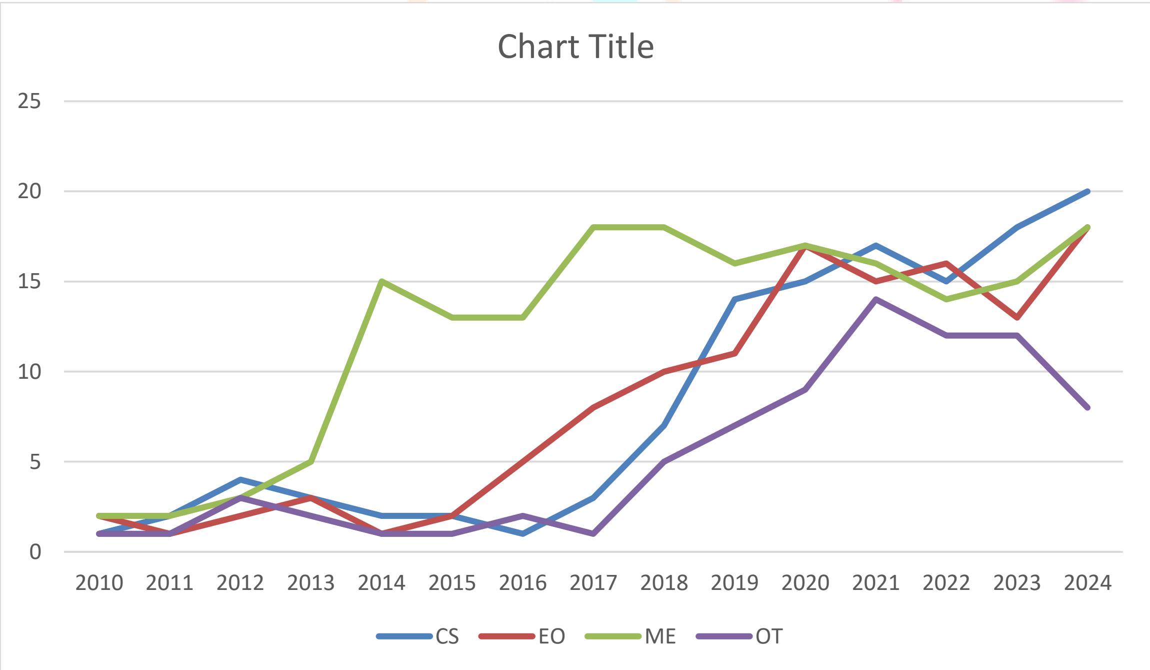


Fig. 4. Fourteen -year trend of publications by disciplinary categories.

4.1 Implications for research

I first offer a systematic interdisciplinary literature review of AI-HRM. Previous research on this issue has been prone to incoherent thinking because there has not been cross-disciplinary integration. As Seeber et al. (2020) aptly contended, "We do not know what we do not know." Closing this gap, my review brings together disparate studies from various disciplines, reviewing them under topic, theory, and methodology perspectives. I identify crucial gaps in existing literature and suggest specific areas that require future scholarly attention. I also introduce an interdisciplinary definition of Artificial Intelligence, which has the consequence of consolidating currently separate avenues of research. This definition can assist scholars in charting the boundaries of AI-HRM research and to formulate more focused research, and aid practitioners to understand the extent and usability of AI for HRM contexts.

Second, my review offers a critical evaluation of the theoretical foundation in existing AI-HRM research and proposes strategic directions for future research. I found that theoretical development is scarce across disciplines, with only 21% of papers I examined employing theory—and many of them superficially (e.g., Faliagka et al., 2014). To enhance the impact and generalizability of future research, more robust theoretical underpinning is required. I propose three strategies:
Collaboration among management and technical scholars to cooperate in creating theoretical frameworks that are both practically relevant and methodologically rigorous.

Development of fresh theory for AI-HRM, with empirical validation and conceptual addition. Four new theories (e.g., Sampson, 2021) and two new theoretical frameworks (e.g., Fleming, 2019) develop in accordance with my review, along with illustrations like Huang and Rust (2018) that show the potential for fresh theoretical contribution.

Third, I advance knowledge of methodological rigor in AI-HRM studies. My review points out several methodological errors in current literature and offers pragmatic recommendations to address them. One of them is data validity, which has been a recurring issue. I recommend researchers to increase measurement validity and employ AI-based research methods to enhance the precision and reliability of conclusions made. Building on previous AI-method papers (for example, Choudhury et al., 2021; Minbashian et al., 2010), I also propose a general framework to synthesize AI methods in future management studies, bridging methodological gaps and fostering the application of high-level tools for HRM research.

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