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The Impact of Artificial Intelligence Bias on Human Resource Management Functions: Systematic Literature Review and Future Research Directions

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ABSTRACT: *Artificial intelligence (AI) has become a valuable tool for facilitating Human Resource Management (HRM) functions. Although, it should be noted that AI has a specific character side away from other technology. Publications covering this knowledge area have grown sharply, however the scholarly covering the impact of AI bias inHRM is scarce. This paper studies this area and goes deeper to explore the future research areas by conducting a systematic literature review for 598 papers from Scopes and Emerald insight databases of which 34 articles were selected after implementing the PRISMA tool and quality evaluation stage. Results generated revealed that biased AI applications are negatively affecting performance management, compensation, staffing and training and development. Apart from that future research domains and questions have been outlined and identified from organizations' and employees' perspectives.*

KEYWORDS: artificial intelligence, human resource management, bias, data, HRM functions

INTRODUCTION

In the business analysis era, the organization needs a confident, fast and creative response with more attention to the competitive landscapes, which may change more rapidly than ever before (Jackson & Dunn-Jensen, 2021). According to this fact, many organizations are embracing emerging technologies aiming to achieve competitive advantages and advanced performance (Ostheimer et al, 2021). Among these technologies, artificial intelligence (AI) has attracted the attention of business organizations by the ability to analyze, synthesize and generate accurate results in a record time (Votto et al, 2021). It's expected to significantly transfer the existing business model, while simultaneously creating new ones (Simon, 2019). According to PwC's global artificial intelligence study, AI could contribute up to $15.7 trillion to the global economy in 2030, more than the current revenue of China and India combined. Of this, $6.6

trillion is likely to come from increased productivity and $9.1 trillion is likely to come from new consumption behavior (PwC, 2017).

AI is introduced as a digital technology with the ability to autonomously perform tasks commonly thought to require human intelligence (Kshetri, 2021). It has been adopted in business organizations since the 1980s, being a goal of investment and efforts of many researchers and scientists to design and develop computer vision systems, natural language process (NLP), artificial neural network (ANN) and expert systems in order to augment organization performance (Borges et al, 2021). Moreover, in the last decade, the massive volume of data generated in different formats caused a revolutionary demand for AI applications, resulting in extracting valued information from variants and unpolished data (Akter, et al., 2021). AI has the ability to interpret data through machine learning algorithms and reach specific goals through adaptable changes to existing knowledge (Qamar et al, 2021). With these features, AI has increasingly become an essential part of many functional sectors in the organization. AI applications such as chatbots, fuzzy systems, genetic algorithms and much more are now adopted in various organization's departments (Haenlein & Kaplan, 2021; Kaplan & Haenlein, 2019).

One organization department that has being empowered by AI applications and has demonstrated a core change in its functionality when adopting AI, is human resource management (HRM) (Pereira et al, 2021). AI has been successfully implemented in several HRM activities such as recruitment and selection (Johnson et al, 2021), employee performance evaluation (Votto et al, 2021), learning and development (Jaiswal et al, 2022) and predicting employees' emotional intelligence (Prentic et al, 2020). However, many scholars highlighted some challenges and obstacles that could affect AI adoption and promote the potential dark side of AI in HRM functions.

AI and data bias is considered the dark side that affects HRM functionalities from different perspectives (Soleimani et al, 2022). These concerns deal with the impact of biased AI decisions on employees and organizations respectively. From the employee perspective, harmful impacts include discrimination against race, ethnicity, gender, and social class. It also extended to cover employee performance, loyalty and career development (Connelly et al, 2021). From an organizational perspective, biased AI decision is linked with a lack of transparency, poor organizational reputation, wrong critical decision and false financial presumptions (Garg et al, 2021). In details, AI is all about interpreting external data and learning from it. If the external data used to train AI is biased or the training model is biased toward a specific group, then such generated result will adversely affect a mass number of employees and decision-makers (Haefner et al, 2021).

The risk contingent with AI bias was a driver for many researchers to lunch many principles and ideas in order to govern AI development and usage (Bankins, 2021). According to Floridi et al. (2018), there are five core principles for managing AI development and adoption, these principles are beneficence, non-maleficence, autonomy, explicability and justice. By focusing on the last principle, they defined justice as the requires AI to promote fair and just outcomes such as eliminating bias and fostering diversity. In a similar spirit, Akter et al. (2021) argued that adopting AI solutions in the HR department should align with the ability of the organization to predict, detect and mitigate potential biases within AI-powered solutions to ensure fairness. This can be achieved by auditing the behavior of underlying algorithms through diverse perspectives validated by empirically sound methodologies. Along a similar line, Rozado (2020) suggests constructing a heterogeneous well-educated workforce and recommends engaging in adversarial collaboration to appropriately scrutinize, detect and address issues of bias to mitigate the risk of harmful impact.

Although there have been several studies analyzing the applications and impact of artificial intelligence, there still remains a lacuna in the existing literature. Prior studies have explored broadly the adverse impact of AI bias on organization performance (Burlina et al., 2021) or identified the source of AI bias without considering the reflection of generated biased information on the overall HRM functions (Akter, et al., 2021; Du & Xie, 2021). Therefore, there is still a perceptible gap in the in-depth understanding of the impact of AI bias on HRM functions.

Due to expanding and diversity of AI applications in HRM, it becomes particularly important to deeply understand the impact of AI bias on the core functions of HRM: performance management, compensation, staffing and training and development (Qamar et al., 2021). This study mainly fulfills the aforementioned need by conducting a systematic literature review (SLR) on AI bias in HRM. SLR analyzes the literature in a systematic manner to comprehend the breadth and depth of the existing body of work and identify gaps to be investigated (Xiao & Watson, 2019). By summarizing, analyzing, and synthesizing a group of related literature, we can provide insights into research trends in emerging and developing fields, thereby contributing in the mapping of future research potentials (Secundo et al., 2020). This study contributes to the academic literature on AI in HRM by proposing a model that illustrates the impact of AI bias on HRM functions, by embedding the source of AI Bias, AI techniques in HRM and the HRM functions (Akter et al., 2021; Qamar et al., 2021). The following research questions quid our review and make the contributions indicated above:

RQ1: What is the impact of AI bias on HRM functions?
RQ2: What are the future research areas of AI bias in the HRM domain?

The rest of the paper is structured as follows. Section 2 presents the theoretical underpinning and academic background of the current study. Methodological details are presented in Section 3, followed by Research profiling in Section 4. The analysis and findings are provided in Section 5. Finally, section 6 presents the conclusion and limitations of the study.

Theoretical and academic background

Within this section, I followed the procedure of Akter et al. (2021) in building his model (Algorithmic biases in Data-driven innovation phases). First, I refer to the diffusion of innovation theory (DOI) to describe how the innovation spread is affected by bias. Then briefly outline the source AI bias and AI techniques in HRM as elements to propose a model for the impact of AI bias on HRM functions.

Diffusion of innovation theory vs. bias

The decision of whether the company will adopt a particular technology and the return of investment (ROI) involved with that decision has been a long source for formulating theories (Molinillo & Japutra, 2017). A number of theories have been used to understand and facilitate the technology adoption process, such as the technology acceptance model (Davis et al., 1989), the technology–organization–environment (TOE) framework (Tornatzky & Fleischer, 1990) and the innovation theory (Rosenberg, 1982). However, diffusion of innovation theory (DOI) is the most common theory that describes the technology adoption process at the organizational level (Molinillo & Japutra, 2017).

DOI theory is proposed by Rogers (1995) and is considered the foundation to know how, why and at what level innovative ideas and technologies could spread among the organization (Hund et al., 2021). He argues that the adoption of emerging technology is impactd by innovation characteristics, such as relative advantage, compatibility, complexity, trialability and observability. Subsequently, Straub (2009) examines these factors against biased decisions generated by innovative technology. The result shows that implicit bias in any stage of technology adoption could destroy the relative advantages as well as increase the complexity of accepting a new technology among employees. Reflecting on this argument, researchers call for deeper investigation and analysis to understand the consensus of biased decisions generated by AI on employees and stakeholders in different organization departments (Ünal & Kılınç, 2021).

Source of AI bias

More and more decision-making processes in organizations are being developed and controlled by the mass scale of data-driven approaches enabled by AI and Machine Learning (ML) algorithms (Pessach & Shmueli, 2021). The motivation toward adopting AI-powered solutions is understood, we expect algorithms to perform better than humans in several domains. It's superior to human processing by interpreting large-scale data in a second and may take more factors into consideration than a human does. Also, it's commonly spread that AI's decision is more neutral and objective than human (Poggenpohl, 2020). This superiority of AI will likely lead to an innovative change in the concept of management and decision-making (Ünal & Kılınç, 2021). However, this superiority could be affected by AI's bias that automatically prejudice based on data provided from different sources (Lin et al., 2021).

Training models or datasets feeding AI applications can lead to algorithm bias (Bedue & Fritzsche, 2022; Howard & Borenstein, 2018). For instance, a pattern within the dataset may not be accurate or may not represent a group from the target population, thus resulting in either sample inadequacy or sample selection bias. In details, selecting a sample from the incorrect population with regard to attributes, traits, values, attitudes and personality may reinforce biased AI decisions (Lee, 2018). Many ethical issues that exist in our communities are finding their way to AI applications that manage and guide employees within our organizations

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(Mullins et al., 2021). Due to this bias, Akter et al. (2021) identified three different scopes of AI bias: 1) Data bias, 2) Method bias, 3) Socio-cultural bias. These points are clearly addressed data products, data collection, collection process, data formatting and labelling procedures. Accordingly, this paper adopts Akter et al. (2021) sources of AI bias (see Figure1) to build the first part of the model that identifies the impact of AI bias on HRM functions.

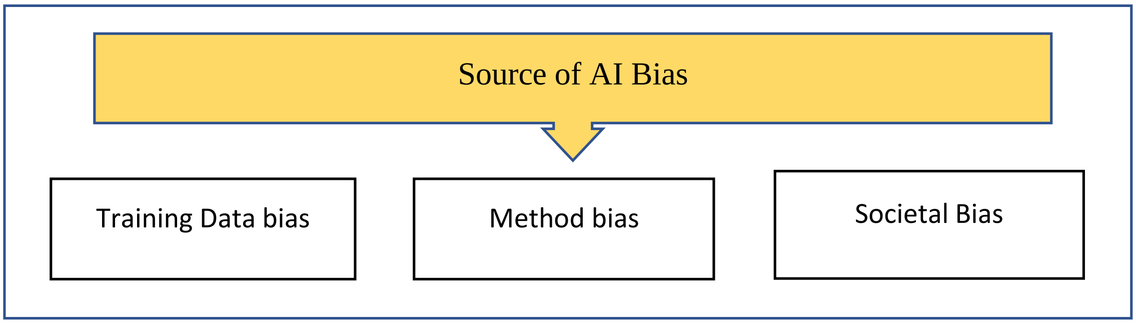

Figure 1 : Source of AI bias

AI applications in HRM functions

AI applications in HRM functions are made to facilitate HR decision-making, employee performance and organization goals based on massive datasets (Black & van Esch, 2020). These data is provided by employees consciously or unconsciously, through wearable devices, sensors and information extracted from social media to build a comprehensive picture on employee performance, attuited and interest (Tambe et al., 2019). It also considered a paradigm shift concentrating on induction and the ability to forecast rather than deduction, as well as a change in data handling and analysis methods using decoding and machine learning algorithms (Garcia-Arroyo & Osca, 2019; Kshetri, 2021).
In the literature, researchers listed six AI applications applied in four primary HRM functions (see Figure 2). These functions are staffing, performance management, compensation and training and development (Devanna et al., 1982; Prikshat et al., 2022; Qamar et al., 2021).

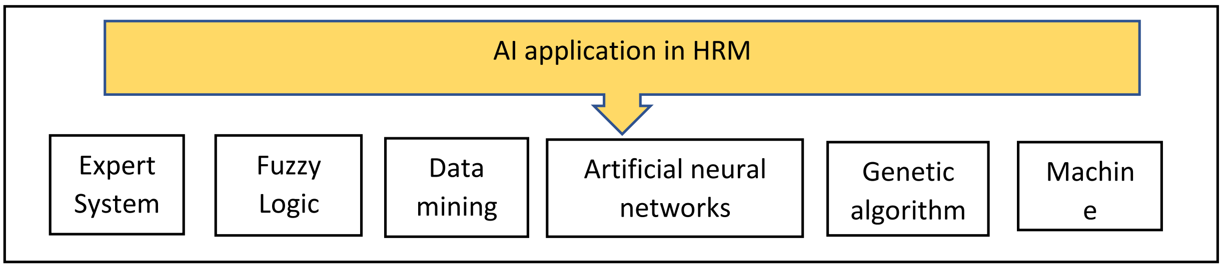

Figure 2: AI applications in HRM

Below is a abbreviated discussion on all six AI applications in HRM functions.

Expert system (ES) in HRM functions.

The features of ES in HRM can be observed in studied scholar as early as 1996, when Lawler and Elliot (1996) explained that ES could facilitate knowledge engineering in most HRM functions such as selection, recruitment and HR planning. Additionally, ES addresses solutions for selected HR problems such as assessment of candidate behavioral and employees' skills as well as supporting decision-making processes for experts' nomination or recruitment systems (Bohlouli, et al., 2017). Therefore, most scientists defined an expert system as a high-tech technology imitating human-expert decision-making (Bohlouli, et al., 2017; Strohmeier & Piazza, 2013). Evidence of the development of ES in HRM is seen in different applications such ID3 algorithm which was introduced as the best-known knowledge-based expert system to present the human mindset based on the decision tree learning idea (Zhang, 2021). BOARDEX is another ES rule-based application for selection through identifying competencies from unstructured data, predicting future expected competencies and providing decision aid for better career development opportunities (Patel et al., 2018).

Fuzzy logic (FL) in HRM functions

Fuzzy set theory is the foundation of fuzzy logic which was introduced by Zadeh (1965). In this theory, the numerical input is represented by a fuzzy variable X which is described by a membership function of F(X). The value F(X) is defining the membership level of the set within 0 and 1. The value of 0 indicates no belongingness to the set, whereas 1 shows absolute belongingness to the set. Any value between 0 and 1 represents the degree of uncertainty that the value belongs to the set (Kimseng et al., 2020).In HRM, FL can be used in staff selection and design (Pereira et al, 2021), differentiate between potential candidates (Serrano-Guerrero et al, 2021) and eliminate bias in evaluating employee performance (Santhosh & Mohanapriya, 2021). In details, expert opinion can work as a fuzzy logic's input which could reflect positively on reasoning capability and improve decision quality (Cabello & Lobillo, 2017).

Data mining (DM) in HRM functions

DM is the process of extracting valuable information from the database, including pattern recognition and association. It helps in different activities such as classification, prediction, outlier analysis, and evolutionary analysis (Liu et al., 2021). In HRM, DM has been used in talent management (Claus, 2019; Liu et al., 2021), employee's performance evaluation (Pereira et al, 2021; Zhang et al 2021), employee recruitement and selection (Chowdhury et al., 2022; Nicolaescu et al., 2020; Votto et al., 2021) and other HRM functions.

Artificial neural networks (ANN) in HRM functions

ANN is a parallel decentralized processing model that simulates the neural function of the human brain. It's a nonlinear, adaptive information processing system composed of a large number of neurons (processing units), layers and networks (Xiang et al., 2022). ANN can predict missing data by conducting self-learning and training to meet the needs of consultant conditions (Mutua, 2022). These characteristics of ANN , as well as their efficiency, robustness and adaptability make them a valuable tool for classification, prediction, decision support and performance analysis. Accordingly, ANN has been used as an intelligent technique in HRM functions to provide a tremendous amount of knowledge to improve managerial decisions in selection (Walczak, 2016), performance and recruitment (Tkáč & Verner, 2016; Yang, 2022).

Genetic algorithm (GA) in HRM functions

J. H. Holland is the first developer of the of GA in 1975 based on evolution operation. These operations are selection, crossover, and mutation operations (Ali et al., 2021). The evaluation principles guide the involved population toward an optimum solution (Ali et al., 2021). GA has been used to solve limited and unconstrained optimization problems that repeatedly modify a population (Koch &̈scher, 2016). In HRM, GA has been used in workforce planning and analysis of candidate's knowledge. For instance, Acharyya and Datta (2020) used GA to solve challenges related to staff transfers using real-life restrictions. Also, Bi and Tang (2022) utilized GA for evaluating employee performance and managing workforce planning.

Machine learning (ML) in HRM functions

ML is learning process in which machines can learn independently and improve their knowledge over time, by fed data and information in the form of observations and real-world interaction without being programmed (Votto et al, 2021). ML is depending on algorithms to achieve its tasks (Rodgers et al., 2022). The algorithm is grouped either by learning style (i.e., supervised learning, unsupervised learning, semi-supervised learning) or by similarity in form or function (i.e., classification, regression, decision tree, clustering, deep learning) (Mallick, 2021). ML applications are widely employed in HRM functions such as recruitment, selection, employee engagement, training and development, performance management, employee turnover, team dynamics and human resource allocation (Garg et al, 2021).

Methodology design

Despite growing academic interest in the role of AI applications in running organizations, little attempt has been made to provide a comprehensive review of AI bias on HRM functions (Tuffaha et al, 2022). To provide an overview of the knowledge-base and to highlight the boundaries of the recent gap, this study has undertaken a SLR to address the RQs. This study adhered to a SLR approach because, unlike a narrative review, the SLR approach aims to overcome the issue of researcher bias often evident in narrative literature reviews, by using a deep search and analysis framework that combines cross-referencing between researchers, research databases and the application of agreed exemption criteria (Alsolai & Roper, 2020; Phillips et al, 2015).

The present study consists of four major phases: identification, screening, eligibility and including. These phases are following the guideline of the PRISMA statement to guarantee the quality of the search and selection process of the scholars (BMJ, 2021). PRISMA primarily focuses on indicating how studies were defined, screening resulted papers and assessing the eligibility of each paper included in the study to acquire relevant information and ideas in order to answer RQs (Figure 3 shows a snapshot of the methodology) (Garcia-Arroyo & Osca, 2019; Mohammad Saif & Md Asadul, 2022). The next sections provide an illustrated overview of the research process adopted in the study.

Designing the research query

Along with this paper, the articles were retrieved from the Scopes Elsevier databases and Emerald Insight databases by looking for English peer-reviewed academic articles. To maintain the quality of this study books, non-peer-reviewed articles, case reports, doctoral dissertations, abstracts, conferences and book chapters were excluded due to the limited peer-review process (Nolan & Garavan, 2016).

To ensure sufficient coverage of articles on the topic of this paper, all relevant keywords mentioned in the previous section (Theoretical and academic background) are included in our search query (Budhwar et al, 2022; Pereira et al, 2021). The final search query is divided into two parts; the first part deals with keywords related to "Source of AI bias and AI applications in HRM", and the second part deals with "HRM functions" aspects. We used both "AND" and "OR" operators to design a comprehensive search query. The final search query was as follow: ("Artificial intelligence bias" OR "Artificial intelligence ethic" OR "AI bias" OR "AI ethic" OR "Machine learning bias" OR "Algorithm bias" OR "Training data bias" OR "Genetic algorithm bias" OR "Artificial neural networks bias" OR "ANN bias" OR "Data mining bias" OR "fuzzy bias" OR "Expert systems bias") AND ("Human Resource Management" OR "HRM" OR "HR" OR "Human Resource" OR "Staffing" OR "Recruiting" OR "Compensation" OR "Performance management" OR "Performance Evaluation" OR "training and development").

The search was performed from January 1980 to October 2022 and generated 598 articles. After discarding the duplicate records, 514 articles were eligible for more screening. The next step consists of the manual screening of 514 articles by checking the compatibility of their titles, abstracts and conclusions with the research scope and RQs. Thirty-six (36) articles passed the manual screening phase and nominate to the quality evaluation phase.

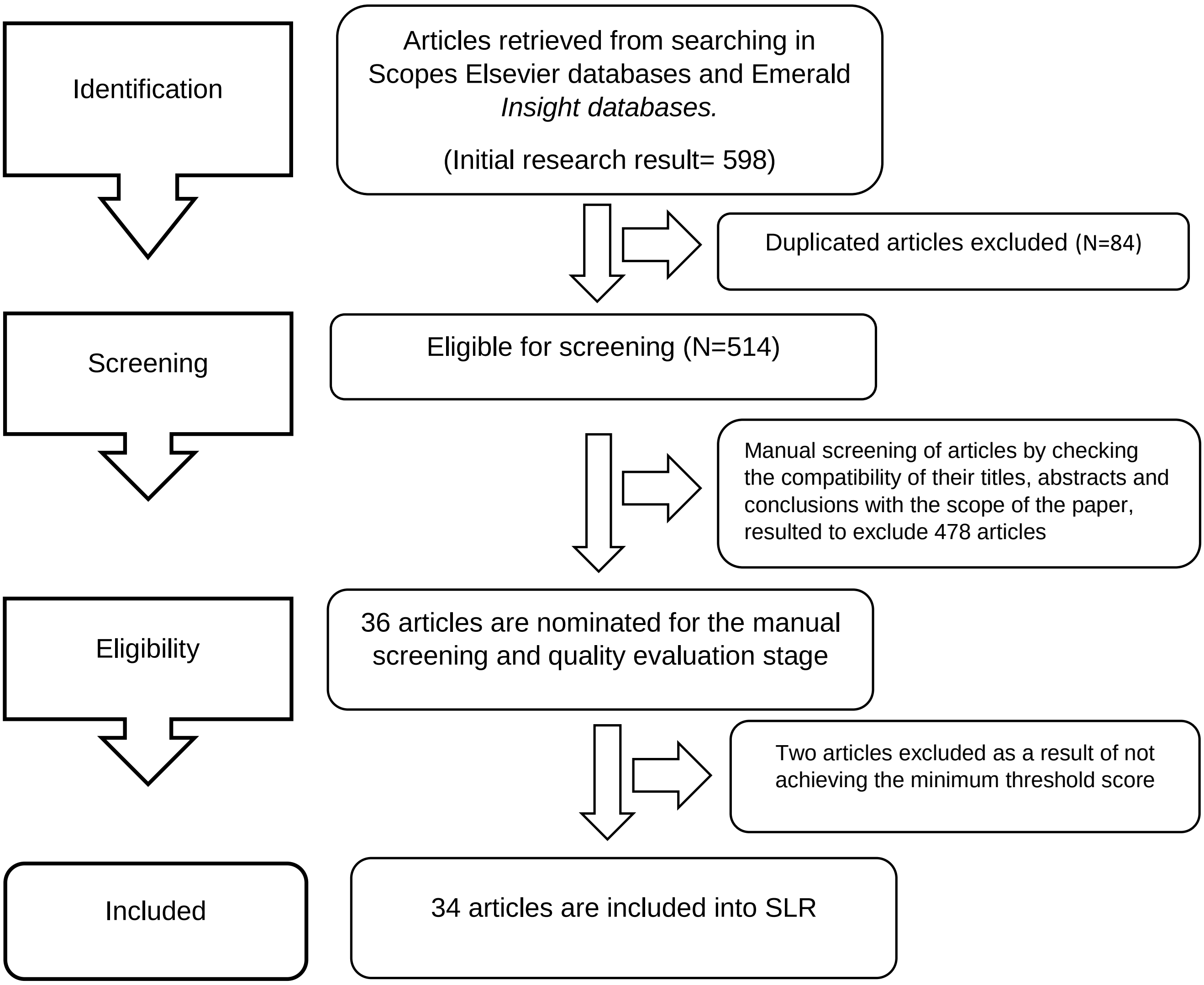

Figure 3. PRISMA flow chart indicating the process of selecting articles included in the review.

Quality evaluation stage and final articles list.

To maintain transparent, insightful and unbiased of the current SLR's results, we asses the quality of each article nominated to the final list. The assessment depends on the five strictquality evaluation (QE) criteria (see table 1) and followed the recommendation of Behera et al (2019). The articles that did not meet the minimum threshold score (4.5) were not considered for further analyses. Two articles were excluded as a result of the low score and the final list comprised of 34 articles. The next step is to extract relative data to address the research questions proposed for this study.

Table 1. Quality evaluation criteria

QE#	Evaluation criteria	Score				
		+0	+1	+1.5	+2	Note
QE 1	Clear evidence for quantitative or qualitative analysis	No evidence	_	Qualitative	Quantitative	
QE 2	Article explicitly discussed the advantages and limitations	No	_	Partially	yes	The score is partial if only one of the study's advantages or limitations is reported
QE 3	The findings of the study are justifiable	No	_	Partially	yes	The score is partial if only very limited techniques are explained or one of the techniques used is not detailed
QE 4	The article was published in a reliable and peer recognition source	TC+H=0	1 ≤ TC+H ≤ 49	50 ≤ TC+H ≤ 100	TC+H > 100	- TCN refers for total citation number - H stands for H index
QE 5	The article compares the proposed method with methods used in prior study	No	yes	_	_	

Strategy of content analysis

In this paper, content analysis was used to interpret and analysis text data through the systematic classification process of coding to present various information on the impact of AI bias on HRM functions in academic literate (Malik & Lenka, 2020). The unit analysis of this research is the selected articles (34 articles) that nominated for reviewing after a systemic search methodology and quality evaluation. Coding templet was developed based on the recommendation of Varma & Dutta (2021), to extract information about:

1) Author name and year of publication.
2) Journal name.
3) Research methodology.
4) AI applications in HRM.
5) Problem scope addressed in the articles.
6) Main findings and contributions to academia on AI bias in HRM functions.

Based on results generated from content analysis, we provide useful insights for decision-makers on the impact of AI bias on HRM function.

Research profiling

We provide descriptive analysis and visualization from information extracted from 34 articles. From year of publication, we revealed that AI HRM is relatively new research field and started in 2018. It's worth highlighting that most articles are published in 2021 and the rest of them are published in 2018,2019, 2020 and 2022 (See figure 4). These articles were published across 26 journals and counted for 97 authors distributed across different countries. Another point worth highlighting that, the significant number of journals do not belong to HRM's domain and this indicates that 1) HRM domain journals may need to focus more on this research area and 2) AI applications in HRM functions become attractive to other researchers from different disciplines.

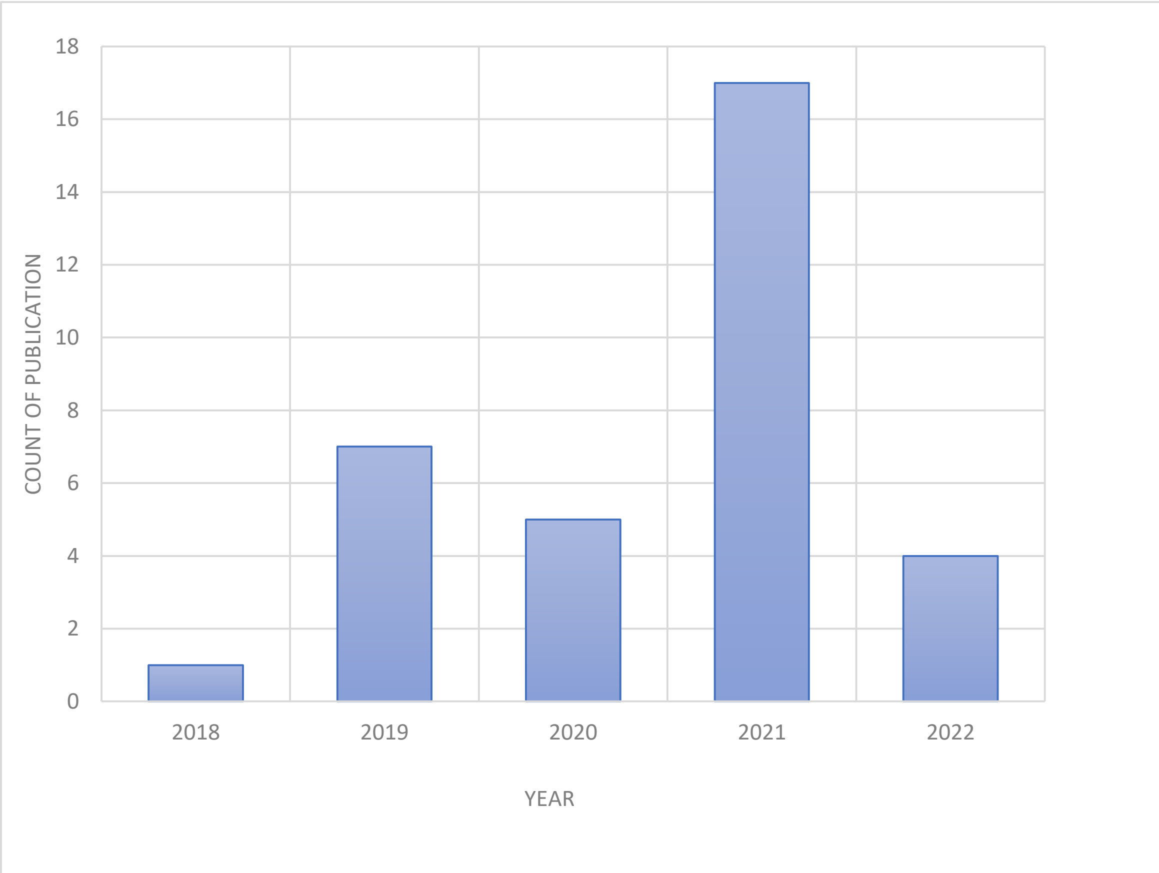

Figure 4: Publications count by year

Considering the top influential articles, Figure 5 shows that (by using overall citation counts and citations per year as indicators to discover the most influential articles) the article "Marketing AI recruitment: The next phase in job application and selection" is the highest total citations and published in "Computers in Human Behavior" journal, the rest of them as shown in Figure 5.

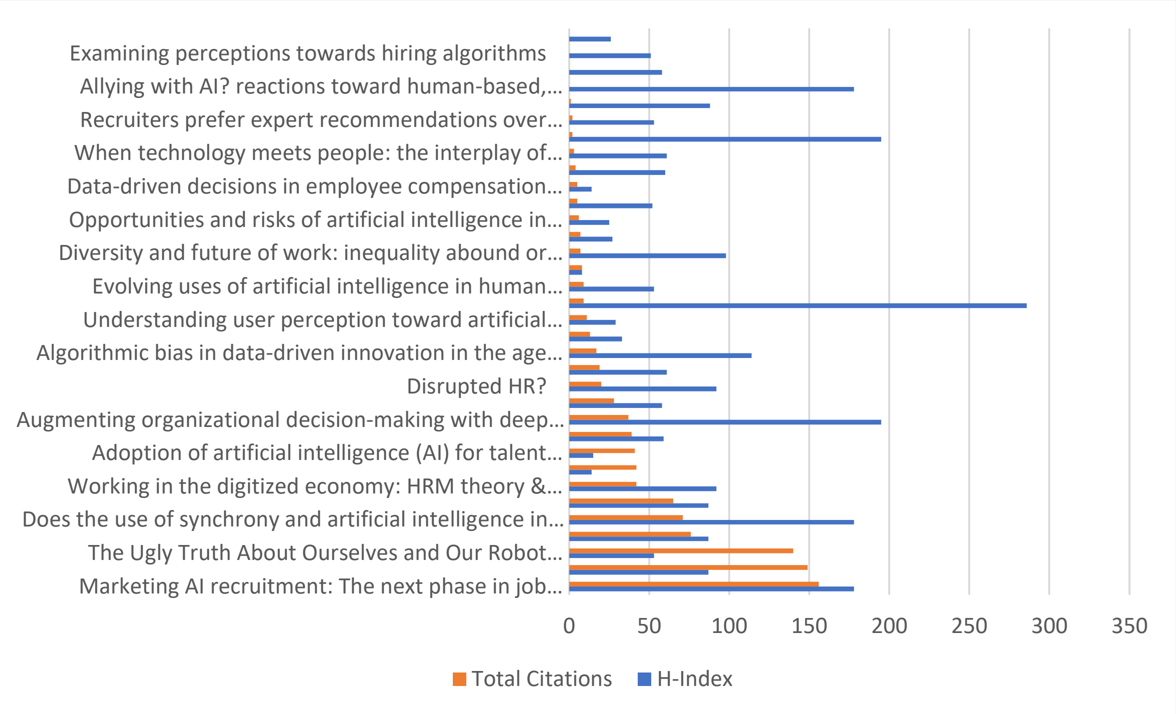

Figure 5: Comparing articles' influencing by total citation and H-index

Methodologically, the articles can be divided into literature review (8.8%), case study (2.9%), conceptual analysis (44.1%), and empirical works (44.1%). Considering empirical work 35.2 % used quantitative analysis and 8.8% used qualitative analysis.

DATA ANALYSIS AND FINDINGS

This section mapped a frame on the sequencies of AI bias on four main HRM functions depending on the sources of AI bias and AI techniques in HRM (Figure 6). Accordingly, target articles are analysed and summarised. Follow, information has been structured to address the set research questions.

The impact of AI bias on HRM functions

Most organizations have their own polices and code of ethics in order to create unbiased culture. To work in parallel with this culture, organizations must address ethical challenges that could affect HRM functions when adopting AI powered applications. Therefore, scholars have identified several challenges affecting main HRM functions as the following:

Impact of AI bias in staffing

The reviewed literature (61.7%) underlined the concern that AI bias can rise serious risks on the functionality of staffing in the HR department (Black & van Esch, 2020; van Esch & Black, 2019). The risk is formulated in a different way, according to Kambur & Akar (2022), ML bias

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reflects on staffing through: 1) Generates wrong decisions and increases the workforce turnover rates in the long run (Pillai & Sivathanu, 2020; Hamilton & Sodeman, 2020); 2) Collapse in arranging the needed quantity and quality of employees (Garg et al, 2021); 3) Disturb recruiting teams to prioritize their time and resources to candidates with significant potential (Oberst et al, 2021; Shrestha et al, 2021); 4) Negative results in terms of testing, video interview and selection decision (Fernández-Martíne & Fernández, 2020; Kshetri, 2021); 5) Wrong performance score associated with biased AI-powered Video interview (Kaplan & Haenlein, 2020; Van Esch et al, 2019); 6) Underestimate qualified candidates, which reflect on their future performance and training needs. Ore & Sposato (2021), raise another concern that affects the repetition of the company. This affection causes irreparable brand damage which leads to perceive less control and fairness on staffing, greater ambiguity and privacy concerns, and less acceptance of AI-led processes among candidates (F. Gonzalez, et al., 2022; Suen et al, 2020). While other scholars go deeper to explain the impact of AI bias on certain underrepresented groups (Lin et al., 2021; Yarger et al., 2020). This impact may appear by labeling datasets (fuel of AI solutions) in a way that encodes discrimination against candidates from specific gender, ethnic, and cultures (Ozkazanc-Pan, 2021; Soleimani, et al. 2022; Yam & Skorburg, 2021).

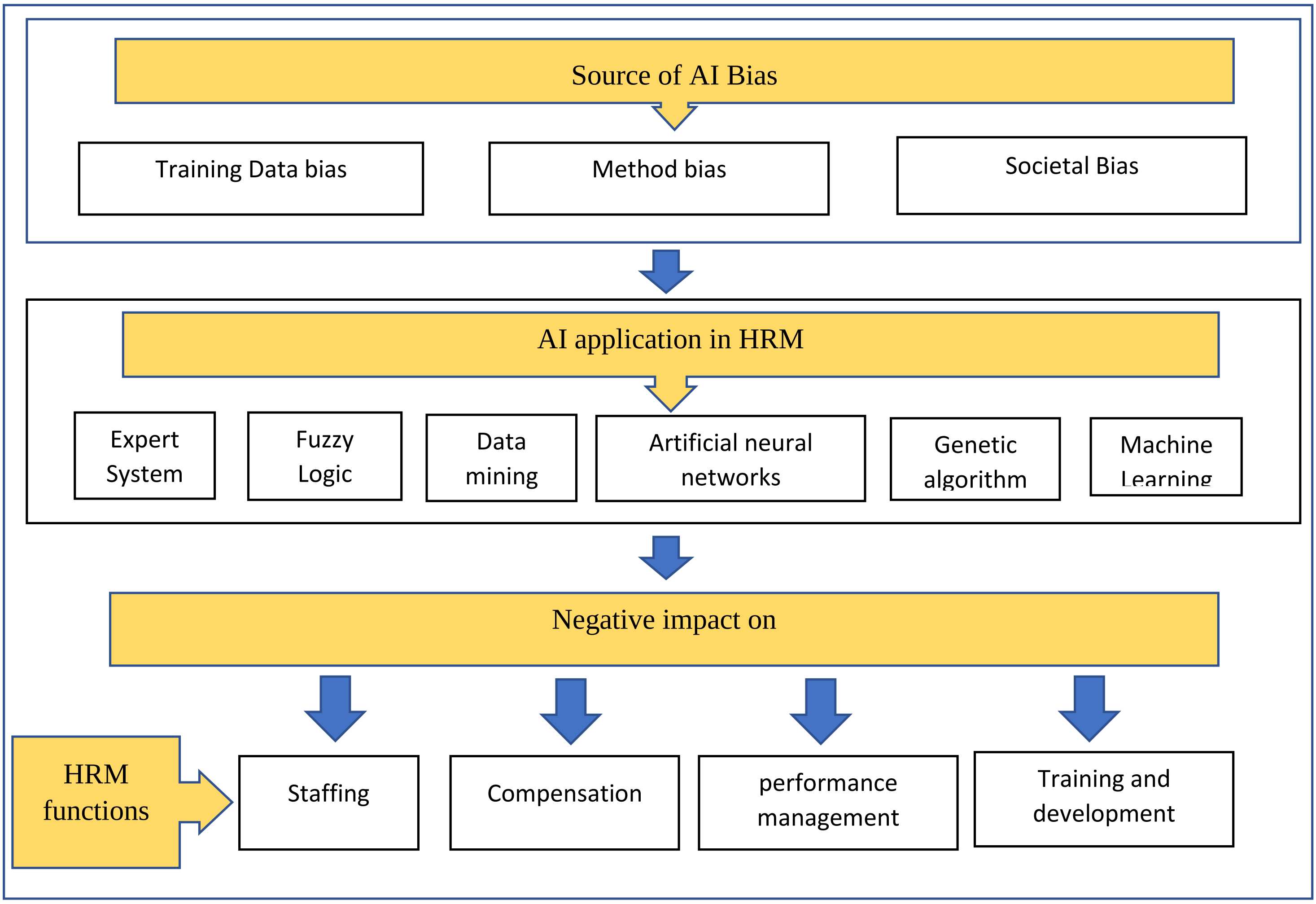

Figure 6: Consequence of AI bias in HRM function

Impact of AI bias on compensation

Compensation is a type of remuneration provided to employees as a result of their job position (Elrehail, et al., 2020). Scholars highlighted the importance of remuneration on employees, for instance Cooke et al. (2020), explained that compensation may impact employees' satisfaction, moral, social life and living position. Accordingly, there is relatively broad agreement that data driven managerial decision would harmly affected when adopting biased AI powered compensation system. This assumption is supported by the following scholars. Connelly et al. (2021), find that biased generated data is affecting on promotion parameters and long-term employee's development plan. In parallel Escolar-Jimenez et al. (2019), emphases on the impact of AI biased decision on organization salary benchmarks against external market conditions. Any manipulation of such sensitive benchmarks can negatively reshape the employees' external and internal living standards, organization reputation and employee's loyalty. Impact of AI bias on performance management

Predicting, managing, analysing and evaluating employee performance is the core function of AI-powered solutions (Ozkazanc-Pan, 2021). In this context, literature underlines the importance of generated data from AI-powered solutions in supporting decision maker by providing key information for strategic performance and developing performance metrics on the key success factors (Raffoni et al., 2018). However, these advantages are limited by the ability of the organization in eliminating biased data generated from AI-solutions (Akter, et al., 2021). As result, our analysis highlighted major consequences of biased AI-solutions on performance management as the following. 1) lack of holistic and heuristic evaluations (Kim & Heo, 2021). 2) negatively affect the effectiveness, trustful and fairness of the organization (Zhang & Yencha, 2022). 3) reduce the reliability of the evaluation process (Minbaeva, 2021). 3) doubt as to whether the assessment is appropriate for different job characteristics (Al-Htaybat & Alberti-Alhtaybat, 2022). 4) lower trust in the quality of the feedback and greater concerns over job displacement risk (Tong et al., 2021). 5) doubts as to whether AI will properly evaluate applicant's capabilities (Akter, et al., 2021).

Impact of AI bias on training and development.

Training and development is another HRM function that can benefit from AI-powered solutions. They help in competency assessment as well as customise training and career planning based on employee's needs (Qamar et al, 2021). The articles studied in this paper argue that handling biased AI decisions is a major factor in promoting this technology within training and development section (Howard & Borenstein, 2018). Studies address a diverse set of disadvantages for biased AI decisions on training and development. These disadvantages are associated with offering biased personalized feedback and self-evaluation (Kashive & Powale, 2021); collapse in defining training needs by irrelative mapping performance ratings and trainee characteristics to relevant KSAs (training style, personality type, knowledge on subject matter, professional experience, etc.); mistake in identifying the learner's preferred method and style of learning; (Maity, 2019; Keyser, et al., 2021).

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Future research areas of AI bias on the HRM domain

Present the future direction of interdisciplinary research on AI bias and HRM function would increase the scholarly attention on this area. In this paper we grouped the proposed future research into two directions. The first direction address organization’s concern, while the second direction address the employee’s concern.

First direction: Organization’s concern.

literature examine different future themes that aid organization on understanding the AI in HRM function. These themes formulated different possible future question as the following: how can organizations ensure that the data quality is sufficient to facilitate the needed analysis while avoiding AI bias?; how can companies monitor the effects of AI decisions in order to mitigate the adverse impact of AI bias?; Under what conditions and to what extent can companies depend sufficiently on integrated AI component?; to what extent do organizations require transparency in reasoning AI components integration?; what is the financial threat of AI bias on organization’s investment and assets?; what are stakeholders’ perceptions (such as customers, recruiters, managers, and staff) toward AI bise?; how should HR department restructure his function and infrastructure to manage data mining and void AI bias?

Second direction: employee’s concern

Another significant area for future research can examine employees’ perspective toward AI bias. In this direction literature address the following research questions as the following: What is the reflection of biased AI decisions on employees’ emotions?; how to balance between massive data usage and personal data privacy rights?; what is the impact of biased hiring algorithms on underrepresented groups behaviours?; do we need from employees to monitor AI decisions to eliminate errors and bias?

CONCLUSION AND LIMITATION OF THE STUDY

Like any emerged technology, AI has advantages and disadvantages. Therefore, HR department has an essential role in understanding this technology by carrying out effective AI adoption and eliminating potential threats. Accordingly, this study carried out a systemic literature review of 34 articles to clarify the reflection of AI bias inHRM functions and the future research of this scope. This LR follows the guideline of the PRISMA statement to guarantee the quality of the search and selection process of the scholars.

Generally speaking, AI applications in HRM functions have increasingly drawn the attention of scholars. However, this study lead to conclude that emerging subject such as AI bias on HRM still needs sophisticated and deep analysis.

In order to understand the consequences of AI bias inHRM, author outline main four HRM functions affected by AI bias depending on the source of AI bias and AI applications in HRM. The conclusions derived from the results obtained are:

First, there is significate challenges associated with biased AI applications on performance management, compensation, staffing and training and development. These challenges construct as a biased decision against candidates and interviewees which threatens the long-term organizational vision. Also, manipulate with compensation databases and salary benchmarks and raise a question of whether performance management in an organization maintains equity and integrity. Besides that, falling on customized accurate training and development programs based on employees' needs. For these reasons, a broader review of bias issues and their reflection will help HR department in considering this technology and managing these issues in a better way. This conclusion is revealed from the fact that using AI-powered applications in the HR department will no longer be optional or buzzword but rather necessary to maintain the competitive advantages of the organization.

Second, in order to expand the practical application of AI in HRM functions, there is a need to highlight the influential future research and new domain that could avoid unexpecting consequences when adopt AI applications in HRM functions . Therefore, this paper present future research areas along with some specific research questions from organization and employees' perspectives.

Finally, HR department requires to update his strategy, functionalities and contribution as indictor of his strategic role in the organization. AI applications and technology is offering a solution for these needs depending on big data and data mining, however not every AI methods is appropriate for HR department. Therefore, HR department should go behind the boundaries by identifying the source of AI bias and the reflection of biased information on the employees to avoid risk, privacy and ethical issue.

In terms of limitation, the result generated in this study should consider the following issues. First, although SLR in this study is covered wide time span in Scopus and Emerald insight, the sample is relatively small as a result of limited scholarly covering AI bias on HRM functions. Second, despite the fact that the author utilized a scientific approach to carry out the current research to ensure accurate and valid results, the possibility of personal bias could pass to the work. Moreover, this study is trying to open new avenues for future research; meta-analysis depending on high-tech contact analysis techniques such as natural language processing (NLP) is essential to provide more specific and accurate insight for guiding future research (Janani & Vijayarani, 2019).

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