INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 05, Issue 04, April 2025, pp : 2606-2611
www.ijprems.com
editor@ijprems.com
e-ISSN : 2583-1062
Impact Factor : 7.001

THE IMPACT OF ARTIFICIAL INTELLIGENCE BIAS ON HUMAN RESOURCE MANAGEMENT FUNCTIONS: SYSTEMATIC LITERATURE REVIEW AND FUTURE RESEARCH DIRECTIONS

Harish S[1], Mohammad Saif N[2]

[1]MBA Student, School of Arts, Humanities and Management, Jeppiaar University, Chennai, India.

[2]Associate Professor, School of Arts, Humanities and Management, Jeppiaar University, Chennai, India

[1]harishsasi619@gmail.com, [2] smileyboysaifu@gmail.com

DOI: https://www.doi.org/10.58257/IJPREMS40600

ABSTRACT

Artificial intelligence (AI) has emerged as a useful instrument for supporting HRM operations. However, it should be mentioned that AI differs from other technologies in a certain way. The number of publications in this field has increased significantly, however there aren't many that discuss how AI bias affects HRM. By conducting a comprehensive literature analysis of 598 papers from the Scopes and Emerald insight databases, 34 articles were chosen after the PRISMA tool and quality evaluation stage were applied. This work investigates this topic and goes further to explore prospective research possibilities. The findings showed that biased AI applications had a negative impact on staffing, training and development, performance management, and compensation.

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

1. INTRODUCTION

The organization must respond confidently, quickly, and creatively in the era of business analysis, paying closer attention to the competitive landscapes, which may change more quickly than in the past (Jackson & Dunn-Jensen, 2021). In light of this, a lot of businesses are adopting new technologies in an effort to get a competitive edge and improve performance (Ostheimer et al, 2021). Because of its capacity to analyse, synthesis, and produce precise findings in a record amount of time, artificial intelligence (AI) has drawn the interest of commercial organizations among these technologies (Votto et al, 2021). It is anticipated that the current business model will be substantially transferred while new ones are also developed (Simon, 2019).

AI is presented as a digital technology that can carry out tasks that are typically believed to require human intelligence on its own (Kshetri, 2021). Several researchers and scientists have been working to design and develop computer vision systems, natural language processing (NLP), artificial neural networks (ANN), and expert systems to improve the performance of business organizations since the 1980s (Borges et al., 2021). Furthermore, the enormous amount of data produced in various formats over the past ten years has led to a revolutionary need for AI applications, which has resulted in the extraction of valuable information from variations and unpolished data (Akter et al., 2021).

Human resource management (HRM) is one organizational area that has benefited from AI applications and shown a fundamental shift in its operations upon implementing AI (Pereira et al, 2021). Numerous HRM tasks, including hiring and selection (Johnson et al., 2021), evaluating employee performance (Votto et al., 2021), learning and development (Jaiswal et al., 2022), and forecasting employees' emotional intelligence (Prentic et al., 2020), have successfully incorporated AI. Nonetheless, a number of academics have pointed out several difficulties and barriers that might influence the adoption of AI and encourage the possible negative aspects of AI in HRM tasks.

From the standpoint of the employee, discrimination based on socioeconomic class, gender, colour, and ethnicity is detrimental. Additionally, it covered career growth, loyalty, and employee performance (Connelly et al., 2021). According to Garg et al. (2021), biassed AI decisions are associated with a lack of transparency, a bad reputation for the organization, incorrect crucial decisions, and erroneous financial assumptions. In specifics, artificial intelligence is all about deciphering and learning from outside inputs. A large number of employees and decision-makers will suffer if the training model or the external data used to train AI is biased towards a certain group (Haefner et al., 2021).

The origin of bias in AI

The mass scale of data-driven techniques made possible by AI and Machine Learning (ML) algorithms is developing and controlling an increasing number of organisational decision-making processes (Pessach & Shmueli, 2021). We anticipate algorithms to outperform humans in a number of areas, which is the driving force behind the adoption of AI-powered products. By analysing vast amounts of data in a split second and possibly accounting for more variables than a human, it outperforms human processing. Additionally, it's often believed that AI decisions are more impartial and objective than those made by humans (Poggenpohl, 2020). The idea of management and decision-making will probably undergo a radical shift as a result of AI's dominance (Ünal & Kılınç, 2021).

Algorithm bias may result from training datasets or models that power AI applications (Bedue & Fritzsche, 2022; Howard & Borenstein, 2018). For example, there may be bias in sample selection or inadequacy if a pattern in the dataset is inaccurate or does not accurately represent a group from the target population. To be more specific, choosing a sample from the wrong population in terms of characteristics, values, attitudes, and personality may support biassed AI judgements (Lee, 2018).

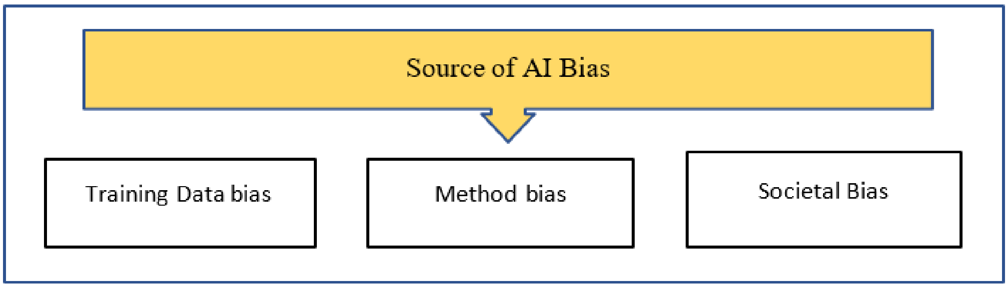

Figure 1: Source of AI bias

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).

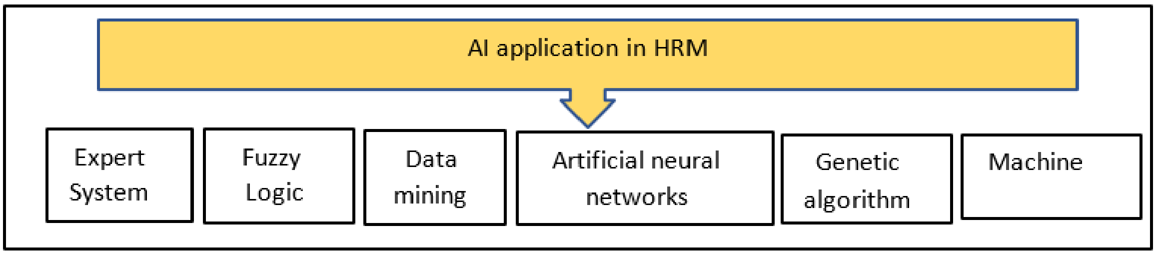

Figure 2: AI applications in HRM

An overview of the six AI applications in HRM functions is provided below.

1. HRM uses Expert Systems (ES)

As early as 1996, when Lawler and Elliot (1996) outlined how ES may support knowledge engineering in the majority of HRM tasks, including hiring, selection, and HR planning, researchers began to notice the characteristics of ES in HRM. Furthermore, ES provides solutions for specific HR issues including evaluating the talents and behaviour of candidates and assisting in the decision-making process for expert nomination or recruitment systems (Bohlouli et al., 2017). According to Bohlouli et al. (2017) and Strohmeier & Piazza (2013), the majority of scientists define an expert system as a high-tech device that mimics human-expert decision-making.

2. The use of Fuzzy Logic (FL) in HRM operations

Zadeh (1965) invented fuzzy logic, which is based on fuzzy set theory. According to this theory, a fuzzy variable X that is specified by a membership function of F(X) serves as the numerical input. The set's membership level between 0 and 1 is defined by the value F(X). A value of 1 denotes complete belongingness to the set, while a value of 0 denotes no belongingness at all. The degree of uncertainty that a value belongs to the set is represented by any value between 0 and 1 (Kimseng et al., 2020). FL can be used in HRM to distinguish between possible applicants and to pick and design staff (Pereira et al., 2021). (Serrano-Guerrero et al., 2021).

3. Datya Mining (DM) in HRM operations

The process of obtaining useful information from a database, such as patterns and associations, is called data mining (DM). It supports a variety of tasks, including evolutionary analysis, categorisation, prediction, and outlier analysis (Liu et al., 2021). DM is used in HRM for a variety of purposes, including hiring and selection (Chowdhury et al., 2022; Nicolaescu et al., 2020; Votto et al., 2021), talent management (Claus, 2019; Liu et al., 2021), and employee performance evaluation (Pereira et al., 2021; Zhang et al., 2021).

4. HRM functions using Artificial Neural Networks (ANN)

An artificial neural network (ANN) is a parallel decentralised processing architecture that mimics how the human brain works.

circumstances (Mutua, 2022). These features of ANN, along with their effectiveness, resilience, and flexibility, make them a useful tool for performance analysis, prediction, categorisation, and decision assistance. As a result, ANN has been applied as an intelligent HRM technique.

5. The role of Genetic Algorithms (GA) in HRM

The first person to develop GA based on evolution operation was J. H. Holland in 1975. According to Ali et al. (2021), these procedures are mutation, crossover, and selection. The evaluation guidelines direct the population in question towards the best possible outcome (Ali et al., 2021).

6. HRM functions using Machine Learning (ML)

Machine learning (ML) is the process by which machines, without programming, may learn on their own and gain knowledge over time by being fed data and information in the form of observations and real-world interactions (Votto et al, 2021). To accomplish its goals, machine learning relies on algorithms (Rodgers et al., 2022). The algorithms are categorised either by similarity in form or function (e.g., classification, regression, decision tree, clustering, deep learning) or by learning style (e.g., supervised learning, unsupervised learning, semi-supervised learning) (Mallick, 2021). Recruitment, selection, training and development, performance management, employee turnover, team dynamics, and human resource allocation are just a few of the HRM tasks that heavily utilise machine learning (ML) technologies (Garg et al, 2021).

2. DESIGN OF METHODOLOGY

Little effort has been made to present a thorough analysis of AI bias on HRM tasks, despite increased scholarly interest in the role of AI applications in managing organisations (Tuffaha et al, 2022). This study has conducted an SLR to answer the RQs in order to give a summary of the knowledge base and to show the limits of the most recent gap. Because the SLR approach, as opposed to a narrative review, uses a deep search and analysis framework that combines researcher cross-referencing, research database use, and the application of established exemption criteria, it attempts to address the problem of researcher bias that is frequently present in narrative literature reviews (Alsolai & Roper, 2020; Phillips et al, 2015). This is why this study followed the SLR approach.

The four main stages of the current study are eligibility, screening, identification, and inclusion. These stages adhere to the PRISMA statement's guidelines to ensure the calibre of the scholars' search and selection procedure (BMJ, 2021). In order to gather pertinent data and ideas to address research questions, PRISMA mainly focusses on defining studies, screening the papers that were produced, and determining the eligibility of each paper that was included in the study (Figure 3 provides a snapshot of the methodology) (Garcia-Arroyo & Osca, 2019; Mohammad Saif & Md Asadul, 2022). An illustrated summary of the research methodology used in the study is given in the following parts.

Creating the research question

All of the pertinent terms listed in the previous section (theoretical and academic background) are included in our search query to guarantee adequate coverage of works on the subject of this paper (Budhwar et al, 2022; Pereira et al, 2021). 598 articles were found during the January 1980–October 2022 search period. 514 articles qualified for additional screening after duplicate records were eliminated. Subsequently, 514 articles are manually screened to ensure that their titles, abstracts, and conclusions align with the research scope and research questions. After passing the manual screening stage, thirty-six (36) items were nominated for the quality evaluation stage.

We evaluate the calibre of each article recommended for the final list in order to preserve the transparency, insight, and objectivity of the current SLR's findings. The evaluation adhered to Behera et al.'s (2019) advice and was based on the five stringent quality evaluation (QE) criteria (see table 1). Articles that fell short of the 4.5 criterion score were not taken into consideration for additional analysis. The final list included 34 items after two were eliminated due to their low score. In order to answer the research questions put out for this study, the next stage is to extract relevant data.

Stage of quality assessment and the final list of articles.

We evaluate the calibre of each article recommended for the final list in order to preserve the transparency, insight, and objectivity of the current SLR's findings. The evaluation adhered to Behera et al.'s (2019) advice and was based on the five stringent quality evaluation (QE) criteria (see table 1). Articles that fell short of the 4.5 criterion score were not taken into consideration for additional analysis. The final list included 34 items after two were eliminated due to their low score. In order to answer the research questions put out for this study, the next stage is to extract relevant data.

www.ijprems.com
editor@ijprems.com
INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 05, Issue 04, April 2025, pp : 2606-2611
e-ISSN : 2583-1062
Impact Factor : 7.001

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	_	_	

3. STRATEGY FOR CONTENT ANALYSIS

This article used content analysis to assess and analyse text data using the systematic classification method of coding in order to provide various insights into how AI bias affects HRM functions in academically literate individuals (Malik & Lenka, 2020). The unit analysis for this study consists of the 34 selected papers that were nominated for review through a methodical search strategy and quality evaluation. As advised by Varma & Dutta (2021), a coding template was made to collect information about:

1) Author's name and year of publication.
2) The journal's name.
3) Research methodology.
4) AI in the administration of human resources.
5) The papers talk about how big the issue is.
6) Important findings and academic works about AI bias in HRM operations.

Profiling research

Using data taken from 34 publications, we offer descriptive analysis and visualization. According to the year of publication, AI HRM is a relatively new subject of study that was initiated in 2018. It is important to note that the majority of the articles were published in 2021, with the remaining ones appearing in 2018, 2019, 2020, and 2022. 97 authors from various nations contributed to these works, which were published in 26 journals. It's also important to note that a substantial portion of publications are beyond the purview of HRM.

4. DATA ANALYSIS AND FINDINGS

Based on the origins of AI bias and AI methodologies in HRM, this part projected a frame on the sequences of AI bias on four primary HRM functions (Figure 6). As a result, target articles are examined and condensed. The following data has been organized to answer the predetermined research questions.

AI bias's effects on HRM operations

To establish an impartial culture, the majority of organisations have their own policies and code of ethics. Organisations must address ethical issues that may impact HRM functions when using AI-powered technologies in order to coexist with this culture. The worry that AI bias may pose major threats to the HR department's personnel operations was

INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 05, Issue 04, April 2025, pp : 2606-2611
www.ijprems.com
editor@ijprems.com
e-ISSN : 2583-1062
Impact Factor : 7.001

highlighted by the examined literature (61.7%) (Black & van Esch, 2020; van Esch & Black, 2019). According to Kambur & Akar (2022), the risk is defined differently, and ML bias affects staffing in the following ways:

1) Leads to poor decisions and eventually higher employee turnover rates (Pillai & Sivathanu, 2020; Hamilton & Sodeman, 2020);

2) Failure to organise the required number and calibre of workers (Garg et al., 2021);

3) Disturb hiring teams to focus their time and resources on candidates with high potential (Oberst et al., 2021; Shrestha et al., 2021);

4) Poor performance in testing, video interviews, and selection (Fernández-Martíne & Fernández, 2020; Kshetri, 2021);

5) Inaccurate performance score linked to biassed AI-powered video interviews (Kaplan & Haenlein, 2020; Van Esch et al, 2019);

6) Underestimate qualified candidates, which affects their performance and training requirements in the future. Ore & Sposato (2021) bring up an additional issue that impacts the company's recurrence.

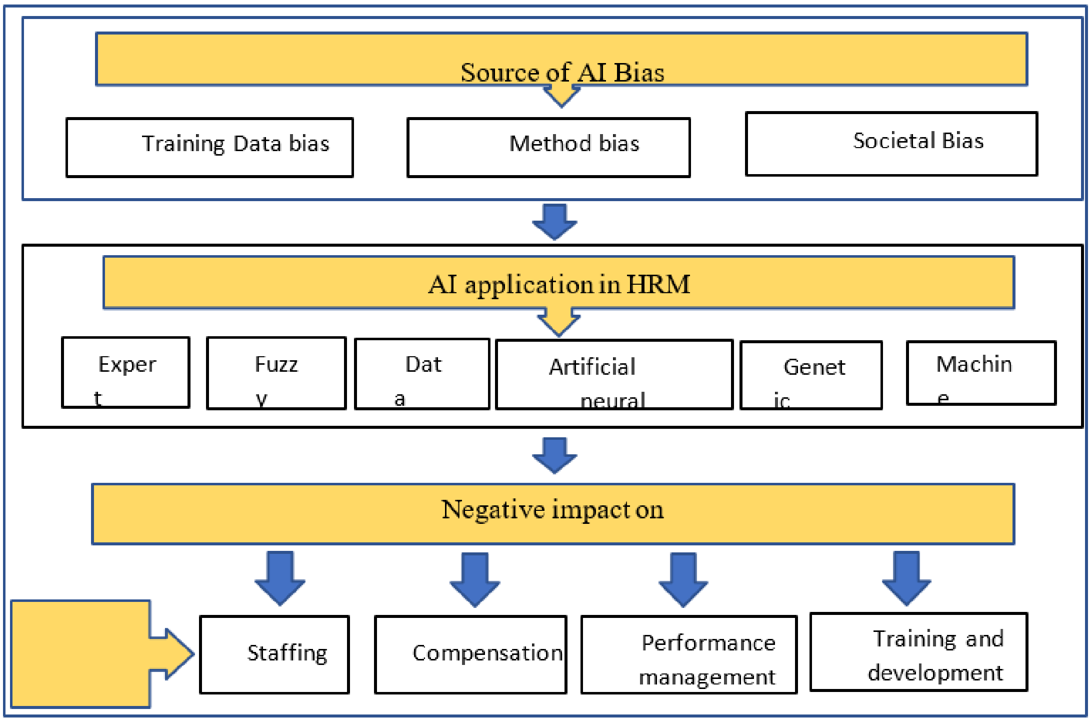

Figure 3: Consequence of AI bias in HRM function

5. CONCLUSION AND LIMITATION OF THE STUDY

AI has benefits and drawbacks, just like any new technology. Therefore, by implementing AI adoption effectively and removing potential hazards, the HR department plays a crucial role in comprehending this technology. In order to shed light on how AI bias is reflected in HRM functions and the direction of future research in this area, this study conducted a systematic literature evaluation of 34 papers. This LR adheres to the PRISMA statement's guidelines to ensure the calibre of the scholars' search and selection procedures.

In general, researchers are becoming more interested in AI applications in HRM tasks. However, this study led to the conclusion that in-depth and comprehensive analysis is still required for emergent topics like AI bias on HRM.

6. REFERENCES

[1] Acharyya, S., & Datta, A. K. (2020). Matching formulation of the staff transfer problem: meta-heuristic approaches. Opsearch, 57, 629–668. doi:10.1007/s12597-019-00432-w

[2] Albert, E. T. (2019). AI in talent acquisition: a review of AI-applications used in recruitment and selection. Strategic HR Review, 18(5), 215-221. doi:10.1108/SHR-04-2019-0024

[3] Al-Htaybat, K., & Alberti-Alhtaybat, L. v. (2022). Enhancing delivery: algorithms supporting performance management in the logistics sector. Qualitative Research in Accounting & Management, 19(3), 305-322. doi:10.1108/QRAM-04-2021-0063

[4] Ali, R., Muhammad, S., & Takahashi, R. H. (2021). Decision making viva genetic algorithm for the utilization

INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 05, Issue 04, April 2025, pp : 2606-2611
www.ijprems.com
editor@ijprems.com
e-ISSN : 2583-1062
Impact Factor : 7.001

of leftovers. International Journal of Intelligent Systems, 36(4), 1746- 1769. doi:10.1002/int.22359

[5] Alsolai, H., & Roper, M. (2020). A systematic literature review of machine learning techniques for software maintainability prediction. Information and Software Technology, 119. doi:10.1016/j.infsof.2019.106214

[6] Bankins, S. (2021). The ethical use of artificial intelligence in human resource management: a decision-making framework. Ethics and Information Technology, 23, 841–854. doi:10.1007/s10676-021-09619-6

[7] Bedue, P., & Fritzsche, A. (2022). Can we trust AI? an empirical investigation of trust requirements and guide to successful AI adoption. Journal of Enterprise Information Management, 35(2), 530-549. doi:10.1108/JEIM-06-2020-0233

[8] Behera, R. K., Bala, K. P., & Dhir, A. (2019). The emerging role of cognitive computing in healthcare: A systematic literature review. International journal of medical informatics, 129, 154-166. doi:10.1016/j.ijmedinf.2019.04.024

[9] Bi, Y., & Tang, M. (2022). Correspondence model of human resource management and marketing based on genetic algorithm. Mobile Information Systems, 2022. doi:10.1155/2022/4152637

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

[11] BMJ. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Research Methods & Reporting, 372(71). doi:10.1136/bmj.n71

[12] Bohlouli, M., Mittas, N., Kakarontzas, G., Theodosiou, T., Angelis, L., & Fathi, M. (2017). Competence assessment as an expert system for human resource management: A mathematical approach. Expert Systems with Applications, 70(15), 83-102. doi:10.1016/j.eswa.2016.10.046

[13] Borges, A., Laurindo, F., Spínola, M., Gonçalves, R., & Mattos, C. (2021). The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions. International Journal of Information Management, 57. doi:10.1016/j.ijinfomgt.2020.102225

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

[15] Xiang, T., Wu, P. Z., & Yuan, S. (2022). Application analysis of combining bp neural network and logistic regression in human resource management system. Computational Intelligence and Neuroscience, 2022. doi:10.1155/2022/7425815

[16] Xiao, Y., & Watson, M. (2019). Guidance on conducting a systematic literature review.

[17] Zhang, Y., Xu, S., Zhang, L., & Yang, M. (2021). Big data and human resource management research: An integrative review and new directions for future research. Journal of Business Research, 133, 34-50. doi:10.1016/j.jbusres.2021.04.019