From Gender Discrimination to Algorithmic Bias: Evolution of Gender Bias Research in Human Resource Management

Annisa Nurahma*
Faculty of Economics and Business, State University of Malang
annisa.nurahma.2104136@students.um.ac.id[1*]

Received 11 August 2026 | Accepted 28 August 2026 | Published 10 September 2026
* Correspondence Author

Abstract
This study aims to map the evolution of gender discrimination research in Human Resource Management (HRM) through a combination of bibliometric analysis and Systematic Literature Review (SLR). Data were collected from the Scopus database using the keywords "gender bias" OR "gender discrimination" OR "gender stereotype". Following the PRISMA 2020 guidelines, 4.492 journal articles published between 1973 - 2025 were selected for bibliometric analysis, while 56 highly relevant studies were further examined through an in-depth SLR. Bibliometric analysis was conducted using VOSviewer to identify publication trends, keyword networks, and thematic structures within the field. The findings reveal a substantial increase in publications on gender bias in HRM, particularly after 2020. The literature is primarily concentrated on themes such as gender equality, workplace discrimination, diversity and inclusion, leadership, glass ceiling, and work–life balance. Furthermore, emerging topics including intersectionality, gender diversity, corporate governance, well being, inclusion, and artificial intelligence have gained increasing scholarly attention. The analysis also indicates a shift in research focus from traditional forms of gender discrimination toward technology-driven concerns, particularly algorithmic bias in HRM practices. This study contributes by providing a comprehensive overview of the intellectual structure, research trends, and future directions of gender bias research in HRM.

Keywords: *Gender Discrimination; Gender Bias; Human Resource Management.*

INTRODUCTION

Research on gender bias in Human Resource Management (HRM) has developed significantly over the past several decades. Various studies have shown that gender bias continues to emerge across HRM practices, ranging from recruitment, selection, promotion, and performance appraisal to career development (Furtado & Moreira, 2021; Hing et al., 2023; Inga et al., 2023). Existing literature has identified various forms of gender inequality in the workplace, including differences in employment opportunities, the gender pay gap, limited access to leadership positions, and gender stereotypes that influence organizational decision-making (Cardel et al., 2020; Chordiya & Hubbell, 2023; Figueiredo et al., 2015; Jagannathan et al., 2024; Lindsay, 2021; Malik & Salles, 2022; Wiedman, 2020). Understanding the evolution of gender bias research in the context of Human Resource Management (HRM) is important for understanding the origins and diversity of gender bias studies, tracing shifts in forms of discrimination from overt to unconscious, improving planning, recruitment, control, and evaluation systems to ensure fairness, and designing inclusive policies that enhance overall employee productivity and retention.

Gender bias is a complex phenomenon because it is influenced not only by individual characteristics but also by social norms, organizational culture, and managerial practices that develop within the work environment (Furtado & Moreira, 2021; Hing et al., 2023; Inga et al., 2023; Naguib & Madeeha, 2023; Rie, 2021; Stamarski et al., 2015). In the HRM context, gender bias can become institutionalized through various organizational policies and procedures that directly or indirectly create differential treatment of men and women. Several studies show that women continue to face barriers to promotion opportunities, equal compensation, and access to leadership positions despite the implementation of various gender equality policies by organizations and governments

(Branicki, 2020; Magliano et al., 2020; Ryan, 2023; Tricco et al., 2024).

The development of the literature also shows that the focus of gender research in HRM has shifted considerably. Early studies generally focused on gender discrimination, the gender pay gap, the glass ceiling, and the representation of women in leadership. In recent years, however, academic attention has shifted toward more complex issues, such as intersectionality, diversity and inclusion, and the use of digital technology and artificial intelligence in HRM practices (Hing et al., 2023; Inga et al., 2023). This development indicates that gender bias is no longer understood solely as a consequence of individual decisions, but may also emerge through the systems and algorithms used in human resource management processes.

Although the number of studies on gender bias in HRM continues to increase, the existing literature is still dominated by empirical studies focusing on specific cases, organizations, or sectors. Consequently, understanding of the intellectual structure, development of research themes, and evolutionary direction of gender bias research in HRM remains relatively fragmented. In addition, there are still limited studies integrating bibliometric analysis with systematic literature review (SLR) to comprehensively map research development while identifying dominant themes, research gaps, and future research agendas.

Previous SLR studies on gender bias in HRM (Hing et al., 2023; Furtado & Moreira, 2021) have mapped types of gender inequality in workplace human resource management processes, as well as their causes and impacts. Other studies (de Lima et al., 2023) have focused on gender bias in the era of Artificial Intelligence. This study found that gender bias in AI is rooted in social and technical factors. Nadeem et al. (2022) focused on decision-making systems and, through an SLR, found that research on gender bias in AI remains limited and underdeveloped. Studies mapping the evolution of gender research from its early development to the AI era remain a gap in the literature. Examining the evolution of gender bias research from its early development to the AI era is necessary to understand the influence of technology on gender bias, shifts in unconscious forms of discrimination, and the development of inclusive and fair policies.

Based on these conditions, this study aims to map the development of research on gender bias in HRM using a combination of bibliometric analysis and SLR. Bibliometric analysis is used to identify publication trends, keyword network structures, and the development of research themes based on Scopus publication data, while the SLR is used to conduct an in-depth synthesis of the most relevant articles. Through this approach, the study is expected to provide a more comprehensive overview of the evolution of gender bias research in HRM, from traditional gender discrimination issues to the emergence of attention to algorithmic bias in modern HRM practices. The findings are expected to enrich the academic literature while serving as a reference for practitioners and policymakers in developing HRM systems that are fairer, more inclusive, and evidence-based. Unlike previous studies, this study does not only focus on gender bias in HRM or gender bias in the AI era, but also: (1) maps the evolution of forms of gender bias from overt discrimination to algorithmic gender bias, and (2) demonstrates the shift from human/organizational bias to technology- and socially based bias.

RESEARCH METHODS

This study was designed to address the lack of comprehensive mapping of research on gender bias in Human Resource Management (HRM) practices, as identified in the introduction, by employing two approaches: bibliometric analysis and systematic literature review (SLR). Bibliometric analysis serves as a rigorous quantitative technique for mapping the development of early gender discrimination studies through the most recent developments (2025), identifying research trends, collaboration patterns, and thematic structures within the field (Zaidi et al., 2025). Meanwhile, the SLR is used for an in-depth analysis of gender discrimination studies published over the last 10 years (2015–2025). Integrating SLR and bibliometric analysis enables not only a quantitative review of the distribution and evolution of gender bias research but also a qualitative examination of dominant themes and research gaps emerging over time.

The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure transparency and systematicity in the literature selection process. This study used publications indexed in the Scopus database to ensure the inclusion of high-quality and internationally recognized research. The literature data were obtained from Scopus, which was selected because it is one of the largest international scientific databases indexing reputable publications across various disciplines. The search process used a combination of title/keywords/abstract: "gender bias" OR "gender discrimination" OR "gender stereotype" (TITLE-ABS-KEY ("gender bias" OR "gender discrimination" OR "gender stereotype")). The search was conducted on April 25, 2026. The search covered all document metadata available in Scopus and yielded 80,174 documents from various fields of study published during 1973–2025.

Screening is an important component of a systematic literature review because it ensures transparency, reproducibility, and rigor in the selection of relevant studies. Following the PRISMA framework, the screening process involved sequential stages of identification, screening, eligibility, and inclusion based on predetermined inclusion and exclusion criteria. This structured screening procedure minimizes selection bias and increases the reliability of review findings compared with a narrative approach. Furthermore, rigorous screening is essential to ensure the validity of the subsequent bibliometric analysis by retaining only relevant and high-quality publications.

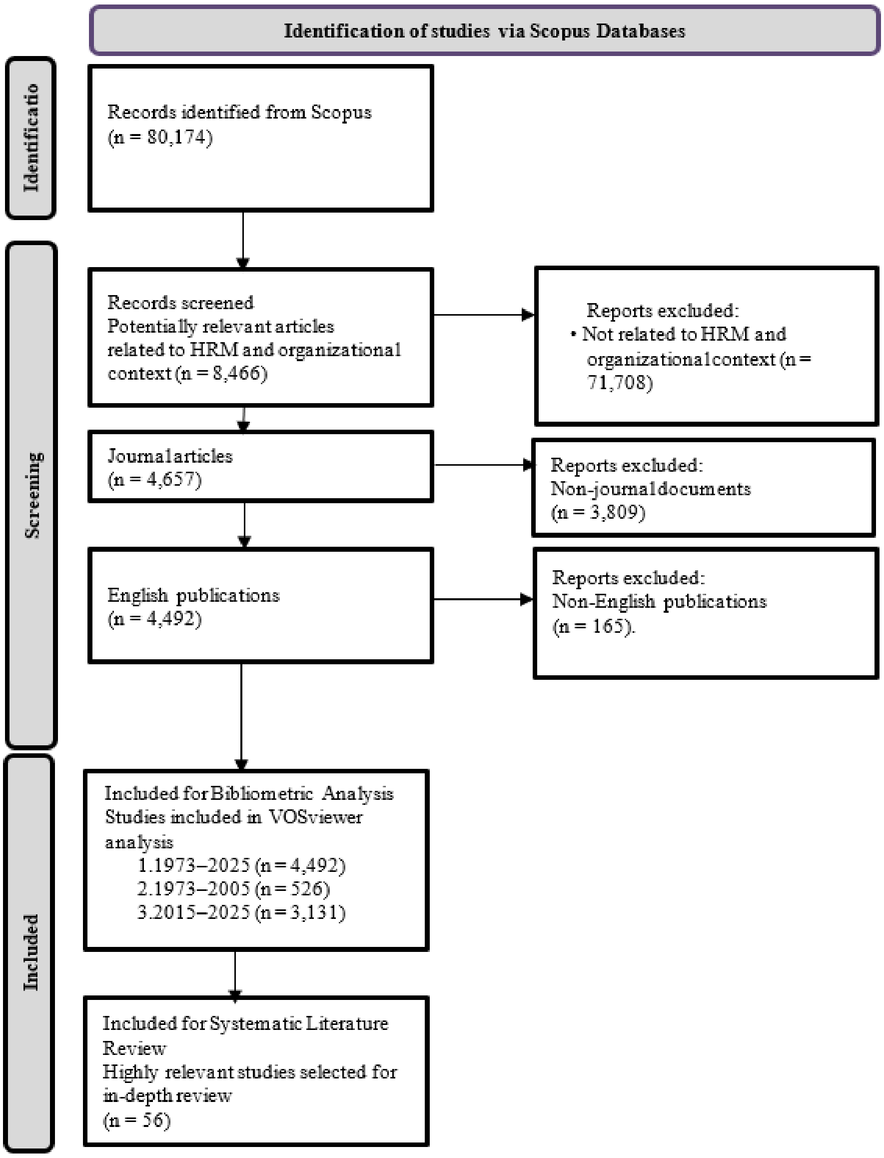

Figure 1. PRISMA 2020 Flow Diagram

At the initial stage, screening was conducted based on the relevance of the research field. Articles focusing on HRM, organizational management, organizational behavior, leadership, employment issues, and related fields such as general management and business were considered. This screening resulted in 8,466 articles relevant to the research focus.

The next stage involved publication-period restrictions to obtain literature more relevant to the development of contemporary research. The publication periods were divided into: (1) no period restriction to understand the overall development of the literature over time (n=4,492), (2) 1973–2005 as the early study period (n=526), and (3) 2015–2025 as the most recent 10-year period (n=3,131). Each period was analyzed bibliometrically using VOSviewer to identify gender bias research trends in HRM and organizational contexts, keyword co-occurrence networks, and research theme clusters. The results were then systematically synthesized to identify major themes, research gaps, and future research directions.

Finally, the 3,131 articles published during 2015–2025 were screened again by adding the keyword artificial intelligence, using the combination: "gender bias" OR "gender discrimination" OR "gender stereotype" AND "artificial intelligence" to identify articles on gender discrimination and its relationship with Artificial Intelligence (AI) bias for inclusion in the SLR. The AI-related search was conducted as a secondary screening stage of the 3,131 publications published during 2015–2025, rather than as an independent search in the Scopus database. Through a review of titles, abstracts, and keywords, 70 articles were identified. Fourteen articles with relatively weak relevance to the research focus were excluded, including articles on factors influencing the choice of AI majors, general HRM trends, sexualization in music videos, and several studies on general AI adoption. Of the 70 articles, 56 were selected as the main references for the SLR analysis. These articles provided the basis for an in-depth discussion of gender discrimination in the Artificial Intelligence era, major themes, research gaps, and future research agendas.

RESULTS and DISCUSSION

Publication Trends

Academically, the roots of gender research can be traced to the work of Simone de Beauvoir (1949) in philosophy, sociology, and women's studies through the book The Second Sex. Early gender research in organizations and the workplace can be traced to Schein (1973) in psychology and organizational behavior, who found that successful managers were often associated with masculinity. Based on the Scopus database, gender studies in HRM began to grow from 1978 through the 1990s, with topics including recruitment discrimination, promotion bias, pay inequality, and the glass ceiling, as reflected in the works of Powell, Anthony Butterfield, Powell, & Butterfield (1979), Rosen & Jerdee (1974), and Tsui & O'Reilly (1989). The evolution of gender bias studies during this era focused on direct discrimination against women in recruitment, promotion, and compensation processes. During this period, researchers sought to demonstrate inequalities in employment opportunities between men and women through labor law, equal employment opportunity, and discrimination theory approaches. The main research focus was to identify whether women received different treatment from men despite having equivalent qualifications.

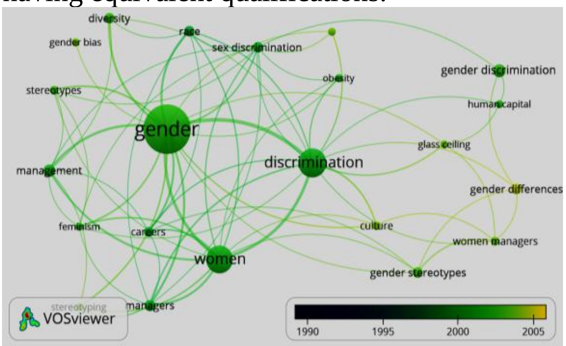

Figure 1. Overlay Visualization of Gender Discrimination Studies (1990–2005)
Source: Processed by the authors using VOSviewer based on the Scopus database

Classical studies of gender discrimination literature in the early period largely focused on bias in core HR practices, such as recruitment, selection, promotion, performance appraisal, and the gender pay gap. The main focus was identifying bias in formal organizational processes. The overlay visualization of gender discrimination studies from 1990–2005 using VOSviewer (Figure 1) shows that the keywords gender, discrimination, and women appear as the largest and most central nodes in the network, indicating that these issues formed the primary foundation of academic discourse related to HRM, leadership, discrimination, and workplace equality. In addition to these three largest nodes, the keywords stereotype, sex discrimination, management, careers, feminism, race, diversity, and gender discrimination also have large node sizes. Classical HRM literature shows that women often face stereotypes related to leadership, technical competence, and work commitment compared with men. These biases may be explicit or implicit and may therefore emerge even when organizations have implemented gender equality policies. As visualized in Figure 1, node size represents the frequency of keyword occurrence, while line thickness (link strength) indicates the degree of association between concepts.

From 2000 to 2005, research attention shifted from explicit discrimination toward subtler psychological and social mechanisms, such as the glass ceiling, gender differences, culture, and women managers (Figure 1). During this phase, HRM studies began to explain how culture and perceptions of leadership, competence, and family roles influence managerial decisions. Research no longer asked only whether discrimination occurred, but also why and through what mechanisms gender bias continued to persist in organizations despite equality policies. The glass ceiling concept became an important theme explaining women's limited access to managerial and leadership positions despite having equivalent competencies. Publications related to gender bias in HRM increased significantly during 2007–2009 and peaked in 2008, but experienced a significant decline in 2010 (Figure 2).

Subsequently, publications related to gender bias in HRM increased more rapidly again over the last decade (2015–2025) (Figure 2), characterized by stable growth indicating that the topic has begun to mature. The increase was also driven by global diversity and inclusion issues. This finding indicates that gender and diversity issues are increasingly integrated into HRM research and have become a major focus of contemporary studies.

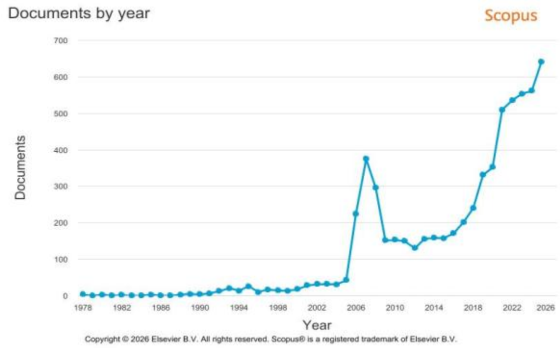

Figure 2. Publication Trends in Gender Bias Research (2015–2025)
Source: Processed from the Scopus database

A significant surge occurred in 2020. The substantial increase after 2020 indicates growing academic attention to gender issues. Publication levels remained high during 2022–2025 and increased sharply in 2025, with new topics such as AI, DEI, and remote work. This trend indicates that gender bias remains relevant and has substantial potential for further development. Publications related to gender bias, diversity, and inclusion have grown more rapidly over the last decade.

The overlay visualization of gender discrimination studies from 2015–2025 using VOSviewer (Figure 3) shows that over the last 10 years, themes such as gender stereotypes, gender discrimination, and gender bias have remained foundational to research on gender inequality and the position of women in organizations. Meanwhile, newer topics shown in yellow, such as intersectionality, gender diversity, corporate governance, well-being, inclusion, and artificial intelligence, still have relatively low frequencies but show increasing trends in recent years. This development indicates a shift in research attention from formal equality issues toward a deeper understanding of the social, cultural, and technological mechanisms that produce gender bias in organizations. In particular, the emergence of artificial intelligence as a relatively new theme indicates that HRM research is entering the digital era, where attention is no longer directed only toward human bias but also toward biases that may emerge in technological systems and algorithms used in human resource management.

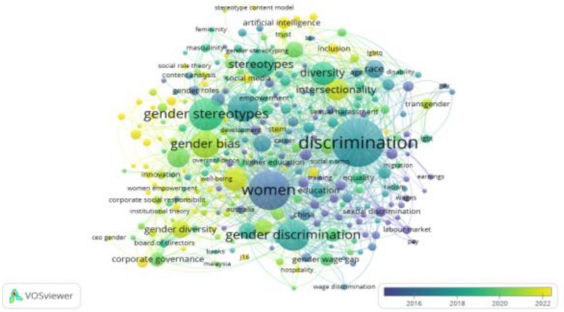

Figure 3. Gender Bias Studies in the Last 10 Years (2015–2025)
Source: Processed from the Scopus database

The network structure (Figure 3) shows a combination of well-established themes and emerging areas. This finding indicates that although gender bias research in HRM has developed extensively, significant opportunities remain for further exploration, particularly in areas with low network density but high conceptual relevance. Therefore, integrating established and emerging clusters is important for developing more comprehensive theoretical and empirical contributions.

Co-occurrence analysis (Figure 4) of keywords in the gender bias literature in Human Resource Management (HRM) shows a conceptual structure divided into several main clusters. Based on the VOSviewer visualization, research on gender bias in the HRM context forms a complex and interconnected thematic network. The keywords gender stereotypes, gender discrimination, gender bias, and women appear as the largest and most central nodes in the network, indicating that these issues form the primary foundation of academic discourse related to HRM, leadership, discrimination, and workplace equality. In addition, the keywords women, diversity, stereotype, and intersectionality also have large node sizes. This indicates that gender research in HRM remains dominated by discussions of women's position in the workplace, forms of discrimination experienced by women, the influence of gender stereotypes on career access and development, and intersectionality, namely the intersection with other issues such as gender discrimination among majority and minority groups (race), people with disabilities, and transgender people.

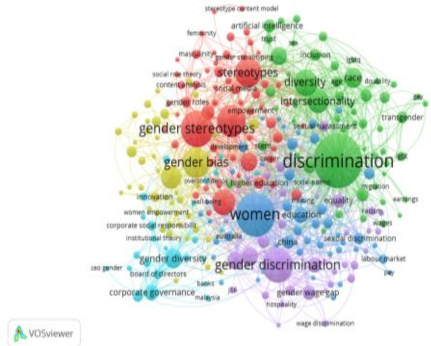

Figure 4. Most Frequently Occurring Keywords in Gender Bias Studies in the Last 10 Years (2015–2025)
Source: Processed from the Scopus database

Interestingly, there is also a cluster linking artificial intelligence, diversity, and gender diversity. In addition, research on Diversity, Equity, and Inclusion (DEI) has developed, highlighting the role of organizational policies in creating inclusive work environments through the keywords diversity, inclusion, and trust. The emergence of this theme indicates the direction of recent research examining how digital technologies and AI-based algorithmic systems can affect HRM practices. The literature has begun to highlight the risk of reproducing gender bias in recruitment algorithms, automated performance evaluation systems, and data-driven decision-making technologies.

Gender Discrimination and Algorithmic Bias Studies

Since the digital era and the development of Artificial Intelligence (AI) in the 2010s, gender bias research has entered a new phase focusing on technology, algorithms, and digital data (Inga et al., 2023; Lambrecht & Tucker, 2019; Trautwein et al., 2025). Researchers have begun examining how AI-based recruitment systems, social media analysis, machine learning, and generative AI can reduce or instead reproduce existing gender bias in historical organizational data (Calabrese, Carrino, Costa, Roberti, & Tiburzi, 2025; Castro-Martínez, Torres-Martín, & Pérez-Ordóñez, 2025; Newstead, Eager, & Wilson, 2023). Research now focuses not only on human bias but also on algorithmic bias, AI fairness, explainability, and interactions among humans, social media, and AI in HRM decision-making (Calabrese et al., 2025; Castro-Martínez et al., 2025; Jiang, Cao, Zhu, & Wang, 2025; Newstead et al., 2023; Song, Park, & Lee, 2025). Thus, the evolution of gender bias research has moved from individual discrimination to structural and psychological bias, and ultimately to the emerging challenge of algorithmic bias in the modern HRM ecosystem.

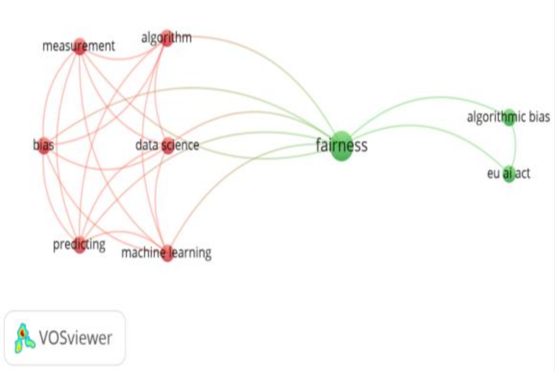

Figure 5. Gender Discrimination Studies Related to Artificial Intelligence in the Last 10 Years (2015–2025)
Source: Processed from the Scopus database

The bibliometric mapping (Figure 5) identified two dominant clusters. The first cluster consists of studies focusing on how AI, LLMs, recommendation systems, and AI-mediated interactions can reproduce gender stereotypes and biased gender representations. The second cluster primarily addresses algorithmic fairness, namely how bias at the data/model level can propagate into algorithmic decision-making processes and produce unequal outcomes. However, through full-paper examination, the researchers identified several studies focusing on how AI bias can be detected, measured, explained, reduced, and controlled through governance.

The clusters were subsequently synthesized through thematic analysis into three analytical themes (Table 1): (1) the emergence of gender bias in AI systems, (2) algorithmic bias, fairness, and discrimination in AI-based decision-making, and (3) AI governance and bias mitigation. The 56 articles were coded based on research focus, type of AI application, form of gender bias, mechanisms through which bias emerges, and proposed mitigation or governance approaches. The initial codes were then grouped into broader conceptual categories. These categories were compared across studies and synthesized into three main themes.

A total of 22 studies (39.3%) were classified under Theme 1, 12 studies (21.4%) under Theme 2, and 22 studies (39.3%) under Theme 3. This distribution indicates that the literature has developed across three interconnected levels: identifying how gender bias emerges, examining how such bias is translated into algorithmic discrimination, and developing mechanisms to detect, mitigate, or regulate the resulting bias.

Theme 1. Emergence of Gender Bias in AI Systems

A total of 22 studies (39.3%) in this category examine how gender stereotypes, representational inequalities, and gender-based assumptions can become embedded in or reproduced through AI applications, including recommendation systems (Ahn et al., 2022), conversational agents, natural language generation, large language models (LLMs), and other AI-mediated interactions (Muñoz-García et al., 2025; Ren et al., 2025). Various systematic reviews have found that AI often reproduces gender bias embedded in historical organizational data (de Lima et al., 2023; Kekez et al., 2025; Nadeem et al., 2022; Varsha, 2023). If training data originate from organizations that have historically recruited more men for certain positions, algorithms may learn these patterns and treat them as indicators of success (Lane et al., 2024). A systematic review of AI recruitment studies shows gender bias at various stages of AI-based recruitment (de Lima et al., 2023).

Studies in this group argue that gender bias in AI cannot be understood solely as a problem of biased algorithms. Instead, bias can emerge from interactions among historical data, model design, language representation, system outputs, and users' interpretation of AI-generated content (Ahn et al., 2022; de Lima et al., 2023; Nadeem et al., 2022). An important development in this theme is the growing attention to LLMs and generative AI (Muñoz-García et al., 2025; Ren et al., 2025). Earlier research often examined recommendation systems, NLP, facial analysis, and automated decision-making systems, whereas more recent studies increasingly investigate gender stereotypes and representational bias in outputs generated by LLMs (de Lima et al., 2023). This demonstrates how AI can reproduce, reinforce, and potentially shape gender stereotypes and representations.

p-ISSN: 2581-2769; e-ISSN: 2598-9502
DOI: http://dx.doi.org/10.32493/JJDP.v10i1.63660

Table 1. Themes in the SLR Analysis

Theme	Number	%	Key References	Findings	Implications
Theme 1. Gendered AI and Reproduction of Gender Bias	22	39.3	(Ahn et al., 2022; Borau et al., 2021; Cao et al., 2025; de Lima et al., 2023; Muñoz-García et al., 2025; Nadeem et al., 2022; Newstead et al., 2023; Pavone & Desveaud, 2025)	Gender bias emerges and is reproduced in AI, LLMs, recommendation systems, and AI-mediated interactions.	Shows how AI can reproduce, reinforce, and potentially shape gender stereotypes and representations.
Theme 2. Algorithmic Bias, Fairness, and Discrimination in AI Decision-Making	12	21.4	(Varsha, 2023; Feldkamp et al., 2024; Lane et al., 2024; Trautwein et al., 2025; Ahn et al., 2022; Bilon, 2025; Cao et al., 2025; Igarashi et al., 2025; Ren et al., 2025)	Bias at the data/model level can propagate into algorithmic decision-making processes and produce discriminatory outcomes.	Shows how algorithmic bias can result in unfair treatment or outcomes across various AI-based decision-making contexts.
Theme 3. AI Governance, Bias Detection, and Mitigation	22	39.3	(Banks et al., 2025; Bansal et al., 2023; Fedele et al., 2024; He et al., 2024; John-Mathews, 2022; Kelley et al., 2022; Slimi & Carballido, 2023; Weber-Lewerenz & Vasiliu-Feltes, 2022)	The literature focuses on developing mechanisms to detect, measure, explain, reduce, and regulate AI bias.	Highlights the importance of bias detection, mitigation, transparency, accountability, and governance in achieving fairer and more responsible AI.
Total	56	100			

Theme 2. Algorithmic Bias, Fairness, and Discrimination in AI Decision-Making

Twelve studies (21.4%) show that gender bias in AI does not only appear in system representations or outputs but can extend to algorithmic decision-making processes. Compared with Theme 1, these studies focus less on whether AI systems represent women and men differently and more on what happens when AI-generated information or predictions are used to make important decisions (Varsha, 2023). Studies in this theme identify bias issues in various contexts, such as recruitment (Feldkamp et al., 2024), training programs (Lane et al., 2024), and other human resource management activities (Trautwein et al., 2025). Thus, bias at the data or model level may propagate into differences in predictions, recommendations, selections, and unfair outcomes.

Many recruitment systems use AI-based algorithms with social media data, candidates' digital footprints, online professional profiles, and professional networking activities (Kelan, 2025; Trautwein et al., 2025). Problems arise when social media data contain gender stereotypes that are subsequently learned by algorithms. If social media data already contain social biases regarding gender roles, AI may amplify these biases during recruitment. Recent research on generative AI shows that large language models (LLMs) continue to produce stereotypical gender associations (Ahn et al., 2022; Bilon, 2025; Cao et al., 2025; Igarashi et al., 2025; Ren et al., 2025). Female candidates are more often associated with emotional and empathetic characteristics, whereas men are associated with strategic and analytical characteristics. These findings indicate that gender bias does not originate solely from humans but may also emerge through interactions between digital social data and AI systems (Bhatt et al., 2025; Kelan, 2025). The literature in this theme also demonstrates the increasing importance of algorithmic fairness in evaluating whether AI systems provide equal treatment and outcomes across gender groups. However, the SLR results show that fairness is not always synonymous with the elimination of gender bias because evaluation results depend heavily on the indicators, decision context, and groups being evaluated. Thus, Theme 2 demonstrates a shift from gender bias as a representation issue to gender bias as a problem of discrimination in algorithmic decision-making.

Theme 3. AI Governance, Bias Detection, and Mitigation

Twenty-two studies (39.3%) discuss various approaches to detecting, measuring, explaining, reducing, and controlling bias in AI systems. These studies include bias detection (Muñoz-García et al., 2025), fair assessment systems (Majrashi, 2025), transparency, explainability, human oversight, and AI governance (Banks et al., 2025). The findings show that growing attention to AI bias is accompanied by the need to establish mechanisms for monitoring and controlling such bias (Banks et al., 2025; Fedele et al., 2024). However, the studies in this theme should not be interpreted as evidence that AI has successfully reduced gender bias. Rather, detection and mitigation approaches have emerged primarily as responses to the risks of bias generated or reproduced by AI (Bansal et al., 2023). Thus, the SLR results reveal a gap between the growing number of proposed methods for addressing bias and the still limited evidence that these interventions can empirically eliminate or consistently reduce gender bias.

Research Gaps and Future Research Agenda

Although research on gender bias and AI is developing rapidly, several gaps remain. Conceptually, the literature has not yet adequately explained how gender bias develops from human decision-making to machine decision-making and human–machine (algorithmic) interaction. The literature indicates that gender discrimination in HRM does not disappear with the introduction of AI. Instead, AI often inherits biases already present in organizational data. Current research has extensively examined gender discrimination in traditional recruitment and algorithmic hiring, but there remains limited understanding of how AI itself becomes a source of bias formation. Most studies still focus on traditional machine learning, while the use of LLMs for screening, interviews, and talent assessment remains relatively new (Ren et al., 2025). Research on candidate perceptions is also limited. Most studies measure algorithmic fairness, while relatively few explore trust in AI recruiters, perceived fairness, and acceptance of AI hiring (Brauner et al., 2025; Tsung-Yu et al., 2024).

Methodologically, current research is generally cross-sectional and therefore cannot explain how gender bias develops over time in continuously learning AI systems. There is also a methodological gap concerning how bias evolves when AI is used repeatedly and adaptively. Empirically, the literature has not reached consensus on questions such as whether LLMs actually provide different candidate recommendations based on gender or whether transparency, explainability, and accountability can reduce perceived gender discrimination. Therefore, future research should develop approaches that integrate HRM and AI to understand and mitigate the reproduction of gender bias in digital human resource management processes.

Based on the systematic literature review results, future research should address several agendas emerging from the development of gender bias research in the context of artificial intelligence. First, empirical research is needed to examine how gender bias in historical data can be transmitted into algorithmic decision-making systems, particularly in recruitment, candidate screening, performance evaluation, and talent management. Second, the development of large language models (LLMs) and generative AI opens a new research agenda concerning the reproduction of gender stereotypes in AI outputs. Third, future studies should develop and test mechanisms for detecting and mitigating algorithmic bias in HRM practices. Fourth, research is needed on AI governance and human–AI decision-making. Future studies could examine whether combining human recruiters with AI produces fairer decisions than decisions made entirely by humans or entirely by AI. Research could also examine how transparency, explainability, accountability, and human oversight affect perceptions of fairness and trust in AI systems used for HRM decision-making. This direction is important because the SLR results show that gender bias is not only related to algorithmic accuracy but also to how algorithmic decisions are used, monitored, and held accountable within organizations.

CONCLUSION

The analysis shows that gender bias is a continuously developing and increasingly relevant topic in HRM research, as indicated by the growing number of publications and the emergence of new themes reflecting changes in the world of work. Early gender discrimination studies (1974–2015), characterized by themes such as stereotype, sex discrimination, management, careers, feminism, race, diversity, and gender discrimination, matured during the last decade (2015–2025) and generated new themes such as intersectionality, gender diversity, corporate governance, well-being, inclusion, and artificial intelligence. The SLR identified several major themes in research on Artificial Intelligence and algorithmic bias, namely AI as a tool for reducing human bias, the reproduction of gender bias through algorithms (algorithmic bias), and LLM bias. These findings show that AI can not only help reduce gender bias in the workplace but can also generate new forms of algorithmic bias related to technological and social factors.

The study provides theoretical implications showing that the evolution of gender bias research in HRM has shifted from a focus on individual discrimination toward attention to bias embedded in digital systems and algorithms. The practical implication for organizations is that they need to audit AI recruitment systems to prevent the reproduction of gender bias originating from historical data.

Although the existing literature is extensive, several important gaps remain underexplored. First, although many organizations have implemented gender equality policies, relatively few studies have empirically evaluated the effectiveness of these policies. Second, technological developments in HRM, such as the use of artificial intelligence in recruitment, have not yet been sufficiently examined from a gender bias perspective, despite their potential to reproduce discrimination systemically. Therefore, future research should integrate more contextual, multidimensional, and socially dynamic perspectives, including the influence of technology and changes in work structures. This approach is expected not only to enrich the academic literature but also to provide practical contributions to designing fairer and more inclusive HRM policies.

This study has limitations. It uses only the Scopus database, so its findings cannot be generalized to other database sources. Future research could use databases other than Scopus. Using more than one database in future studies could provide broader literature coverage and enable comparisons across databases. Second, bibliometric results depend heavily on the keywords and search strategy used. Differences in terminology used by researchers to describe gender bias, artificial intelligence, algorithmic bias, and other forms of discrimination may cause some relevant publications to remain unidentified. Therefore, future research could expand the combination of keywords and use multiple search strategies to test the robustness of the mapping results.

BIBLIOGRAPHY

1. Ahn, J., Kim, J., & Sung, Y. (2022). The effect of gender stereotypes on artificial intelligence recommendations. *Journal of Business Research*, *141*, 50–59. https://doi.org/10.1016/j.jbusres.2021.12.007
2. Akter, S., Dwivedi, Y. K., Biswas, K., Michael, K., Bandara, R. J., & Sajib, S. (2021). Addressing Algorithmic Bias in AI-Driven Customer Management. *Journal of Global Information Management*, *29*(6). https://doi.org/10.4018/JGIM.20211101.oa3
3. Banks, G. C., Tonidandel, S., Dou, W., Gerson, M. J., Xu, D., & Yavorsky, J. E. (2025). How to Reduce Bias in the Life Cycle of a Data Science Project. *Journal of Business and Psychology*, *40*(6), 1253–1273. https://doi.org/10.1007/s10869-025-10022-x
4. Bansal, C., Pandey, K. K., Goel, R., Sharma, A., & Jangirala, S. (2023). Artificial intelligence (AI) bias impacts: classification framework for effective mitigation. *Issues in Information Systems*, *24*(4), 367–389. https://doi.org/10.48009/4_iis_2023_128
5. Beauvoir, S. de. (1949). *The second sex (C. Borde & S. Malovany-Chevallier, Trans.)*. Vintage Books.
6. Bhatt, P., Singh, T., Pavlopoulos, V., & Pham, H. (2025). Decoding Sentiments: Unveiling AI-Generated Content Through Sentiment Analysis and Human Evaluation. *Journal of Global Information Management*, *33*(1). https://doi.org/10.4018/JGIM.394505
7. Bilon, X. J. (2025). Sociodemographic biases in employment decision-making by large language models: experimental evidence from ChatGPT simulations. *Journal of Decision Systems*, *34*(1). https://doi.org/10.1080/12460125.2025.2599912
8. Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases

humanness perceptions of bots and acceptance of AI. *Psychology and Marketing*, *38*(7), 1052–1068. https://doi.org/10.1002/mar.21480

9. Branicki, L. J. (2020). COVID-19 , ethics of care and feminist crisis management. *Gender Work Organ*, *27*, 872–883. https://doi.org/10.1111/gwao.12491
10. Brauner, P., Glawe, F., Liehner, G. L., Vervier, L., & Ziefle, M. (2025). Mapping public perception of artificial intelligence: Expectations, risk–benefit tradeoffs, and value as determinants for societal acceptance. *Technological Forecasting and Social Change*, *220*. https://doi.org/10.1016/j.techfore.2025.124304
11. Calabrese, A., Carrino, S., Costa, R., Roberti, E., & Tiburzi, L. (2026). Exploring the Impact of Generative AI in Detecting Biases and Discrimination in Job Advertisements. *Corporate Social Responsibility and Environmental Management*. https://doi.org/10.1002/csr.70618
12. Cao, X., Li, H., Xu, Q., & Zhu, R. (2025). Detecting Gender Stereotype Biases Against Women Entrepreneurs in Large Language Models. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-025-06216-1
13. Cardel, M. I., Dhurandhar, E., Yarar-Fisher, C., Foster, M., Hidalgo, B., McClure, L. A., Pagoto, S., Brown, N., Pekmezi, D., Sharafeldin, N., Willig, A. L., & Angelini, C. (2020). Turning Chutes into Ladders for Women Faculty: A Review and Roadmap for Equity in Academia. *Journal of Women's Health*, *29*(5), 721–733. https://doi.org/10.1089/jwh.2019.8027
14. Castro-Martínez, A., Torres-Martín, J.-L., & Pérez-Ordóñez, C. (2025). Class, gender and race stereotypes reproduced by generative AI: recommendations for users. *Encontros Bibli*, *30*. https://doi.org/10.5007/1518-2924.2025.e103518
15. Cecere, G., Jean, C., Le Guel, F., & Manant, M. (2024). Artificial intelligence and algorithmic bias? Field tests on social network with teens. *Technological Forecasting and Social Change*, *201*. https://doi.org/10.1016/j.techfore.2023.123204
16. Chordiya, R., & Hubbell, L. (2023). Fostering Internal Pay Equity Through Gender Neutral Job Evaluations: A Case Study of the Federal Job Evaluation System. *Public Personnel Management*, *52*(1), 25–47. https://doi.org/10.1177/00910260221124866
17. de Lima, R. M., Pisker, B., & Corrêa, V. S. (2023). Gender Bias in Artificial Intelligence A Systematic Review of the Literature. *Journal of Telecommunications and the Digital Economy*, *11*(2), 8–31. https://doi.org/10.18080/jtde.v11n2.690
18. Fedele, A., Punzi, C., & Tramacere, S. (2024). The ALTAI checklist as a tool to assess ethical and legal implications for a trustworthy AI development in education. *Computer Law and Security Review*, *53*. https://doi.org/10.1016/j.clsr.2024.105986
19. Feldkamp, T., Langer, M., Wies, L., & König, C. J. (2024). Justice, trust, and moral judgements when personnel selection is supported by algorithms. *European Journal of Work and Organizational Psychology*, *33*(2), 130–145. https://doi.org/10.1080/1359432X.2023.2169140
20. Figueiredo, H., Rocha, V., Biscaia, R., & Teixeira, P. (2015). Gender pay gaps and the restructuring of graduate labour markets in Southern Europe. *Cambridge Journal of Economics*, *39*(2), 565–598. https://doi.org/10.1093/cje/bev008
21. Furtado, J. V, & Moreira, C. (2021). Gender Affirmative Action and Management : A Systematic Literature Review on How Diversity and Inclusion Management Affect Gender Equity in Organizations. *Behavioral Sciences*, *11*, 21. https://doi.org/10.3390/bs11020021
22. He, J., Lin, N., Bai, Q., Liang, H., Zhou, D., & Yang, A. (2024). Towards fair decision: A novel representation method for debiasing pre-trained models. *Decision Support Systems*, *181*. https://doi.org/10.1016/j.dss.2024.114208
23. Hing, L. S. S., Sakr, N., Sorenson, J. B., Stamarski, C. S., Caniera, K., & Colaco, C. (2023). Human Resource Management Review Gender inequities in the workplace: A holistic review of organizational processes and practices. *Human Resource Management Review*, *33*(3), 100968. https://doi.org/10.1016/j.hrmr.2023.100968

24. Hurlin, C., Pérignon, C., & Saurin, S. (2024). The Fairness of Credit Scoring Models. *Management Science*, *72*(1), 406–425. https://doi.org/10.1287/mnsc.2022.03888
25. Igarashi, A., Kano, Y., & Miwa, H. (2025). ChatGPT versus humans in judging discriminatory scenarios: experimental evidence from a Japanese context. *Humanities and Social Sciences Communications*, *12*(1). https://doi.org/10.1057/s41599-025-06054-6
26. Inga, K., Storm, L., Katharina, L., Anna, E., Clar-novak, M., & Louise, S. (2023). Human Resource Management Review Unconscious bias in the HRM literature : Towards a critical-reflexive approach. *Human Resource Management Review*, *33*(3), 100969. https://doi.org/10.1016/j.hrmr.2023.100969
27. Jagannathan, R., Camasso, M. J., & LaFleur, J. (2024). Gender pay gaps in the young adult labor force: prejudice-based discrimination or misreading of the observed-to-offered wage relationship? *Oxford Economic Papers*, *76*(4), 1168–1188. https://doi.org/10.1093/oep/gpae009
28. Jiang, L., Cao, J., Zhu, G., & Wang, Y. (2026). Exploring attribution bias in LLMs: Social influences and prompt-based mitigation. *Technology in Society*, *87*. https://doi.org/10.1016/j.techsoc.2026.103361
29. John-Mathews, J.-M. (2022). Some critical and ethical perspectives on the empirical turn of AI interpretability. *Technological Forecasting and Social Change*, *174*. https://doi.org/10.1016/j.techfore.2021.121209
30. Kekez, I., Lauwaert, L., & Begičević Ređep, N. (2025). Is artificial intelligence (AI) research biased and conceptually vague? A systematic review of research on bias and discrimination in the context of using AI in human resource management. *Technology in Society*, *81*. https://doi.org/10.1016/j.techsoc.2025.102818
31. Kelan, E. K. (2025). Man-versus-machine: gender and technology in discourses on the future of work. *Gender in Management*. https://doi.org/10.1108/GM-09-2024-0513
32. Kelley, S., Ovchinnikov, A., Hardoon, D. R., & Heinrich, A. (2022). Antidiscrimination Laws, Artificial Intelligence, and Gender Bias: A Case Study in Nonmortgage Fintech Lending. *Manufacturing and Service Operations Management*, *24*(6), 3039–3059. https://doi.org/10.1287/msom.2022.1108
33. Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of stem career ads. *Management Science*, *65*(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093
34. Lane, J. N., Lakhani, K. R., & Fernandez, R. M. (2024). Setting Gendered Expectations? Recruiter Outreach Bias in Online Tech Training Programs. *Organization Science*, *35*(3), 911–927. https://doi.org/10.1287/orsc.2022.16499
35. Lindsay, R. (2021). Gender-Based Pay Discrimination in Otolaryngology. *Laryngoscope*, *131*(5), 989–995. https://doi.org/10.1002/lary.29103
36. Magliano, D. J., Mace, V. G., Ellis, T. M., & Calkin, A. C. (2020). Addressing Gender Equity in Senior Leadership Roles in Translational Science. *American Chemical Society*, *3*, 773−779. https://doi.org/10.1021/acsptsci.0c00056
37. Mahajan, S., Agarwal, R., & Gupta, M. (2025). Algorithmic Bias Under the EU AI Act: Compliance Risk, Capital Strain, and Pricing Distortions in Life and Health Insurance Underwriting. *Risks*, *13*(9). https://doi.org/10.3390/risks13090160
38. Majrashi, K. (2025). Employees' perceptions of the fairness of AI-based performance prediction features. *Cogent Business and Management*, *12*(1). https://doi.org/10.1080/23311975.2025.2456111
39. Malik, R. D., & Salles, A. (2022). Debunking Four Common Gender Equity Myths. In *European Urology* (Vol. 81, Number 6, pp. 552–554). Elsevier B.V. https://doi.org/10.1016/j.eururo.2022.02.019
40. Milkau, U. (2023). Is algorithmic credit scoring a "high risk"? *Journal of Digital Banking*, *7*(3), 249–265. https://doi.org/10.69554/BYMQ1790
41. Muñoz-García, V., Consuegra-Ayala, J. P., & Moreda, P. (2025). Leading and non-leading prompts: Quantifying gender bias in Large Language Models through

BiasBloom corpus. *Knowledge-Based Systems*, *325*. https://doi.org/10.1016/j.knosys.2025.113915

42. Nadeem, A., Marjanovic, O., & Abedin, B. (2022). Gender bias in AI-based decision-making systems: a systematic literature review. *Australasian Journal of Information Systems*, *26*. https://doi.org/10.3127/AJIS.V26I0.3835
43. Naguib, R., & Madeeha, M. (2023). Women's Studies International Forum "Making visible the invisible": Exploring the role of gender biases on the glass ceiling in Qatar's public sector. *Women's Studies International Forum*, *98*(March), 102723. https://doi.org/10.1016/j.wsif.2023.102723
44. Newstead, T., Eager, B., & Wilson, S. (2023). How AI can perpetuate – Or help mitigate – Gender bias in leadership. *Organizational Dynamics*, *52*(4). https://doi.org/10.1016/j.orgdyn.2023.100998
45. Pagano, T. P., Loureiro, R. B., Lisboa, F. V. N., Cruz, G. O. R., Peixoto, R. M., Guimarães, G. A. D. S., Oliveira, E. L. S., Winkler, I., & Nascimento, E. G. S. (2023). Context-Based Patterns in Machine Learning Bias and Fairness Metrics: A Sensitive Attributes-Based Approach. *Big Data and Cognitive Computing*, *7*(1). https://doi.org/10.3390/bdcc7010027
46. Pavone, G., & Desveaud, K. (2025). Gendered AI in fully autonomous vehicles: the role of social presence and competence in building trust. *Journal of Consumer Marketing*, *42*(2), 240–254. https://doi.org/10.1108/JCM-05-2024-6865
47. Powell, D. Anthony Butterfield, Powell, G. N., & Butterfield, D. A. (1979). The "good manager": Masculine or androgynous? *Academy of Management Journal*, *22*, 395–403. https://doi.org/10.1177/1059601192171004
48. Ren, R., Xu, Y., Yao, X., & Cole, S. T. (2025). Whose journey matters? Investigating identity biases in large language models (LLMs) for travel planning assistance. *Current Issues in Tourism*. https://doi.org/10.1080/13683500.2025.2609218
49. Rie, S. K. (2021). Perspective Gender bias in academia: A lifetime problem that needs solutions. *Neuron*, *109*, 2047–2074. https://doi.org/10.1016/j.neuron.2021.06.002
50. Rosen, B., & Jerdee, T. H. (1974). Effects of applicant's sex and difficulty of job on evaluations of candidates for managerial positions. *Journal of Applied Psychology*, *59*(4), 511–512. https://doi.org/10.1037/h0037323
51. Ryan, M. K. (2023). Addressing workplace gender inequality: Using the evidence to avoid common pitfalls. *Br J Soc Psychol.*, *62*, 1–11. https://doi.org/10.1111/bjso.12606
52. Schein, V. E. (1973). The relationship between sex role stereotypes and requisite management characteristics. *Journal of Applied Psychology*, *57*(2), 95–100. https://doi.org/10.1037/h0037128
53. Slimi, Z., & Carballido, B. V. (2023). Navigating the Ethical Challenges of Artificial Intelligence in Higher Education: An Analysis of Seven Global AI Ethics Policies. *TEM Journal*, *12*(2), 590–602. https://doi.org/10.18421/TEM122-02
54. Song, Y. J., Park, J., & Lee, S. K. (2026). Disappointed with Siri: Expectation–experience gaps in human–AI interaction. *Technological Forecasting and Social Change*, *225*. https://doi.org/10.1016/j.techfore.2026.124540
55. Stamarski, C. S., Hing, L. S. S., & Elacqua, T. C. (2015). Gender inequalities in the workplace : the effects of organizational structures , processes , practices , and decision makers ' sexism. *Frontiers in Psychology*, *6*(September), 1–20. https://doi.org/10.3389/fpsyg.2015.01400
56. Trautwein, Y., Zechiel, F., Coussement, K., Meire, M., & Büttgen, M. (2025). Opening the "black box" of HRM algorithmic biases – How hiring practices induce discrimination on freelancing platforms. *Journal of Business Research*, *192*. https://doi.org/10.1016/j.jbusres.2025.115298
57. Tricco, A. C., Parker, A., Khan, P. A., Nincic, V., Robson, R., Macdonald, H., Warren, R., Cleary, O., Zibrowski, E., Baxter, N., Burns, K. E. A., Coyle, D., Ndjaboue, R., Clark, J. P., Langlois, E. V, Ahmed, S. B., Witteman, H. O., & Graham, I. D. (2024). Interventions on gender equity

in the workplace : a scoping review. *BMC Medicine*, 1–12. https://doi.org/10.1186/s12916-024-03346-7

58. Tsui, A. S., & O'Reilly, C. A. (1989). Beyond Simple Demographic Effects: The Importance of Relational Demography in Superior-Subordinate Dyads. *Academy of Management Journal*, *32*, 402–423. https://doi.org/10.2307/256368
59. Tsung-Yu, H., Yu-Chia, T., & Chien Wen (Tina), Y. (2024). Is this AI sexist? The effects of a biased AI's anthropomorphic appearance and explainability on users' bias perceptions and trust. *International Journal of Information Management*, *76*. https://doi.org/10.1016/j.ijinfomgt.2024.102775
60. Varsha. (2023). How can we manage biases in artificial intelligence systems – A systematic literature review. *International Journal of Information Management Data Insights*, *3*(1). https://doi.org/10.1016/j.jjimei.2023.100165
61. Weber-Lewerenz, B., & Vasiliu-Feltes, I. (2022). Empowering Digital Innovation by Diverse Leadership in ICT – A Roadmap to a Better Value System in Computer Algorithms. *Humanistic Management Journal*, *7*(1), 117–134. https://doi.org/10.1007/s41463-022-00123-7
62. Wiedman, C. (2020). Rewarding Collaborative Research: Role Congruity Bias and the Gender Pay Gap in Academe. *Journal of Business Ethics*, *167*(4), 793–807. https://doi.org/10.1007/s10551-019-04165-0
63. Zaidi, M., Amiruddin, B., Samsudin, A., Suhandi, A., Cos, B., & Prahani, B. K. (2025). Social Sciences & Humanities Open Scientific mapping and trend of conceptual change : A bibliometric analysis. *Social Sciences & Humanities Open Journal*, *11*(October 2024), 101208. https://doi.org/10.1016/j.ssaho.2024.101208

