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Mapping Gender Bias and Workplace Inclusion in Artificial Intelligence-Based Recruitment: A Bibliometric Co-Occurrence

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A R T I C L E I N F O

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A B S T R A C T

This study aims to systematically map the research landscape of gender bias and inclusion in Artificial Intelligence (AI)-based recruitment by identifying dominant themes, conceptual relationships, and existing research gaps. It addresses the fragmentation of prior studies that often examine AI, bias, and inclusion as separate domains. Using a bibliometric approach with keyword co-occurrence analysis, data were collected from Scopus-indexed journal articles published between 2016 and 2025 and analyzed using VOSviewer to visualize keyword networks, identify thematic clusters, and examine research trend evolution. The results indicate a strong conceptual relationship between AI, gender bias, recruitment decision-making, and inclusion, where gender bias acts as a mediating mechanism influencing recruitment decisions and subsequently determining workplace inclusion outcomes. This study contributes theoretically by proposing an integrated conceptual framework that positions AI-based recruitment as a socio-technical system connecting technological processes, algorithmic bias, and inclusion outcomes.

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INTRODUCTION

The rapid integration of Artificial Intelligence (AI) into recruitment processes has significantly transformed contemporary human resource management practices. AI-driven systems are increasingly utilized to automate resume screening, predict candidate–job fit, and enhance decision-making efficiency. These technologies enable organizations to process large volumes of applicant data with greater speed and consistency compared to traditional recruitment methods. As a result, AI is often perceived as a tool that can improve objectivity and reduce human bias in hiring decisions (Acemoglu & Restrepo, 2018; Black & van Esch, 2020; Chopal & Garg, 2021; Do & Oblina, 2025; Upadhyay & Khandelwal, 2018).

Despite these advantages, a growing body of research highlights that AI-based recruitment systems are not inherently neutral. Instead, they may reproduce or even amplify existing social inequalities embedded within historical data (Jobin et al., 2019; Mehrabi et al., 2021; O'Neil, 2016; Selbst et al., 2019). In particular, gender bias has emerged as a critical concern in algorithmic decision-making. Prior studies demonstrate that AI systems trained on biased datasets tend to replicate patterns of discrimination, especially in contexts where certain occupations have historically been dominated by specific genders (Barocas & Selbst, 2016; Buolamwini & Gebru, 2018; Caliskan et al., 2017; Danks & London, 2017). Furthermore, the opacity of complex machine learning models complicates efforts to detect and mitigate such biases, raising concerns about fairness, accountability, and transparency (Floridi et al., 2018; Mehrabi et al., 2021; Wachter et al., 2020).

In parallel, the concept of workplace inclusion has gained increasing attention in organizational research. Inclusion extends beyond diversity by emphasizing individuals' sense of belonging, recognition, and equal participation within organizational processes (Daniel & Dorin, 2024; Shore et al., 2011). From this perspective, recruitment serves as a critical entry point in shaping inclusive workplaces. However, when AI-driven recruitment systems systematically disadvantage certain groups, they may undermine organizational efforts to foster inclusion, thereby creating a paradox between technological efficiency and social equity (Daniel & Dorin, 2024; Irfan et al., 2024; Mittelstadt, 2016; Nishii, 2013).

Although previous studies have examined AI in recruitment, gender bias in algorithmic systems, and inclusion as separate research streams, the integration of these three domains remains fragmented. Existing literature tends to focus either on the technical aspects of AI implementation or on ethical concerns in isolation, without systematically mapping how these themes are interconnected within the broader scholarly landscape (Binns, 2018; Cowgill, 2020; Jobin et al., 2019; Raghavan et al., 2020). Moreover, bibliometric studies in this area are still limited, particularly those that specifically analyze the co-evolution of AI, gender bias, and inclusion in recruitment contexts. This lack of integrative analysis results in an incomplete understanding of dominant research themes, conceptual linkages, and underexplored areas (Sari, 2024; Zhou et al., 2022).

To address this gap, this study employs a bibliometric approach using co-occurrence analysis to systematically map the literature on gender bias and inclusion in AI-based recruitment. Bibliometric analysis is useful for identifying research trends, thematic structures, and conceptual relationships within a field through the quantitative evaluation of scholarly publications (Donthu et al., 2021; Zhou et al., 2022). By analyzing publications indexed in Scopus between 2016 and 2025, this research aims to identify dominant thematic clusters, examine conceptual relationships among key topics, and uncover emerging research trends. In doing so, the study seeks to provide a comprehensive and structured overview of the field.

This research contributes to the literature in three main ways. First, it offers a systematic mapping of fragmented research at the intersection of AI, gender bias, and inclusion, thereby clarifying the intellectual structure of this domain. Second, it identifies research gaps and emerging themes that can guide future investigations. Third, it provides insights for practitioners and policymakers by highlighting the implications of AI-driven recruitment for fairness and inclusion, supporting the development of more transparent and equitable hiring systems (Binns, 2018; Floridi et al., 2018; Raghavan et al., 2020).

THEORETICAL REVIEW

This section synthesizes key theoretical and empirical studies related to Artificial Intelligence (AI)-based recruitment, gender bias in algorithmic systems, and workplace inclusion. Rather than treating these topics as isolated domains, this review emphasizes their conceptual interconnections and highlights how they collectively shape contemporary recruitment practices (Binns, 2018; Jobin et al., 2019; Raghavan et al., 2020).

Artificial Intelligence (AI) in Recruitment

The adoption of Artificial Intelligence (AI) in recruitment represents a significant shift in human resource management, enabling organizations to enhance efficiency and consistency in hiring decisions. AI technologies, including machine learning, natural language processing, and data analytics, are widely used to automate resume screening, candidate matching, and preliminary assessment (Acemoglu & Restrepo, 2018; Chopal & Garg, 2021; Upadhyay & Khandelwal, 2018). These systems are often perceived as tools that can minimize human subjectivity and improve decision-making accuracy (Black & van Esch, 2020; Do & Oblina, 2025).

However, the assumption of algorithmic objectivity has been critically challenged in recent literature. AI systems are inherently dependent on the quality and structure of training data, which often reflect historical hiring practices and organizational preferences (Barocas & Selbst, 2016; Blustein, 2019; O'Neil, 2016). Consequently, rather than eliminating bias, AI may encode and reproduce existing inequalities in a more systematic and less visible manner. Furthermore, the complexity of algorithmic models introduces issues of opacity or "black-box" decision-making, limiting transparency and accountability (Jobin et al., 2019; Mehrabi et al., 2021; Selbst et al., 2019; Wachter et al., 2020).

Gender Bias in AI Recruitment System

Gender bias in AI has become a central concern in discussions of algorithmic fairness. Bias in AI systems typically originates from historical data that reflect existing social inequalities, which are then learned and perpetuated by machine learning models (Barocas & Selbst, 2016; Caliskan et al., 2017; Danks & London, 2017). In recruitment contexts, this may result in systematic disadvantages for certain gender groups, even when candidates possess comparable qualifications (Cowgill, 2020; Roy, 2017).

Empirical studies show that algorithmic bias can emerge through linguistic patterns, data imbalance, and model design choices (Noble, 2018). Moreover, , Buolamwini & Gebru (2018) demonstrate how AI systems may produce unequal outcomes across demographic groups. These findings indicate that gender bias is not merely a technical flaw but a socio-technical issue shaped by the interaction between data, algorithms, and human decision-making (Mehrabi et al., 2021; Mittelstadt, 2016; O'Neil, 2016).

Inclusion in Organizational Context

Workplace inclusion has become a strategic priority in modern organizations. Inclusion refers to the extent to which individuals feel valued, respected, and able to participate fully in organizational processes (Daniel & Dorin, 2024; Shore et al., 2011). Unlike diversity, which focuses on representation, inclusion emphasizes fairness in experiences and opportunities (Irfan et al., 2024; Nishii, 2013).

In recruitment, inclusion is directly influenced by how candidates are evaluated and selected. Biased recruitment systems can restrict access for underrepresented groups and reinforce structural inequalities (Daniel & Dorin, 2024; Irfan et al., 2024; Shore et al., 2011). The integration of AI into recruitment intensifies this challenge, as algorithmic decisions may scale bias if not properly monitored and controlled (Floridi et al., 2018; Jobin et al., 2019; Wachter et al., 2020).

Integrating AI, Gender Bias, and Workplace Inclusion

Although AI, gender bias, and inclusion have been widely studied, research integrating these three dimensions remains fragmented. Existing studies tend to focus either on technical performance or ethical concerns without systematically connecting these aspects (Binns, 2018; Cowgill, 2020; Jobin et al., 2019; Raghavan et al., 2020).

From a theoretical perspective, AI-based recruitment can be understood as a socio-technical system in which technological tools interact with organizational values and social structures (Mittelstadt, 2016; Selbst et al., 2019). Within this system, gender bias plays a critical role in shaping how AI outputs influence recruitment decisions, while inclusion represents the broader outcome reflecting fairness and equity (Binns, 2018; Floridi et al., 2018; Raghavan et al., 2020).

Conceptual Framework

Based on the synthesis of previous studies, this research proposes a conceptual framework to explain the relationship between Artificial Intelligence (AI), gender bias, recruitment decision-making, and workplace inclusion.

AI-based recruitment systems function as the primary technological driver that determines how candidate data are processed, evaluated, and ranked during the hiring process. These systems rely heavily on historical datasets and algorithmic models, which may inherently contain embedded biases related to gender and other social inequalities.

Within this system, gender bias operates as a mediating variable that emerges from biased data, algorithmic design, and human intervention. This bias influences how AI systems interpret candidate information and shape the fairness and objectivity of recruitment outcomes.

Recruitment decision-making represents the operational stage where AI-generated outputs are translated into actual hiring actions. At this stage, biased algorithmic recommendations may affect candidate evaluation, shortlisting, and final selection decisions, even when applicants possess comparable qualifications.

Recruitment decision-making is positioned between gender bias and workplace inclusion because hiring decisions represent the practical stage where algorithmic recommendations are converted into organizational action. Even when AI systems generate biased outputs, exclusion does not occur automatically until these outputs influence actual recruitment decisions such as candidate shortlisting, interview selection, and final hiring choices. Therefore, recruitment decision-making serves as the direct mechanism through which algorithmic gender bias affects inclusion outcomes.

Workplace inclusion is conceptualized as the final outcome variable, reflecting the extent to which recruitment processes create fair, equitable, and inclusive opportunities for diverse candidates. Inclusive outcomes depend on the ability of organizations to identify, monitor, and mitigate bias throughout AI-driven recruitment systems. The proposed conceptual relationship can be illustrated as follows:

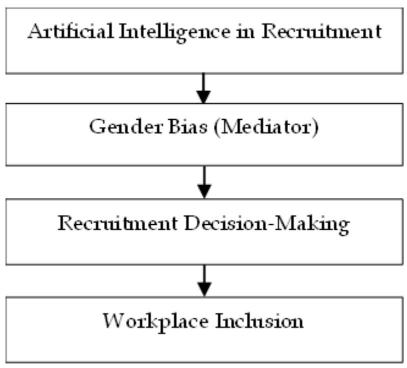


Figure 1. Conceptual Framework

This framework highlights that the relationship between AI and workplace inclusion is indirect and mediated by gender bias and recruitment decision-making processes. It further suggests that improving inclusion in AI-based recruitment requires interventions at multiple levels, including data quality, algorithm design, transparency, and organizational oversight.

By integrating technological, social, and organizational dimensions, this framework offers a conceptual contribution to understanding AI-driven recruitment as a socio-technical system. It also provides the theoretical foundation for the bibliometric analysis conducted in this study.

METHODOLOGY

This study employs a quantitative research design using a bibliometric approach to systematically map the literature on gender bias and inclusion in Artificial Intelligence (AI)-based recruitment. Bibliometric analysis is particularly suitable for identifying research trends, intellectual structures, and conceptual relationships within a specific field through the quantitative evaluation of published studies (Zhou et al., 2022).

The data for this study were collected from the Scopus database, which is widely recognized as one of the most comprehensive and reliable sources of peer-reviewed academic publications. The data retrieval process was conducted on June 4, 2025.

To ensure the relevance of the dataset, a structured search query was applied using the TITLE-ABS-KEY field in Scopus. The search string used in this study was as follows:

(TITLE-ABS-KEY ("artificial intelligence" OR "AI") AND TITLE-ABS-KEY ("recruitment" OR "hiring") AND TITLE-ABS-KEY ("gender bias" OR "bias") AND TITLE-ABS-KEY ("inclusion" OR "diversity")).

The search was limited to articles published in English between 2016 and 2025, considering that significant developments in AI-based recruitment have emerged during this period. Only journal articles were included to ensure the quality and academic rigor of the dataset.

To enhance the validity of the analysis, specific inclusion and exclusion criteria were applied. Articles were included if they:

1. Focused on AI or algorithmic systems in recruitment or hiring contexts,
2. Addressed issues related to bias, discrimination, or fairness, and
3. Discussed inclusion, diversity, or equality in organizational settings.

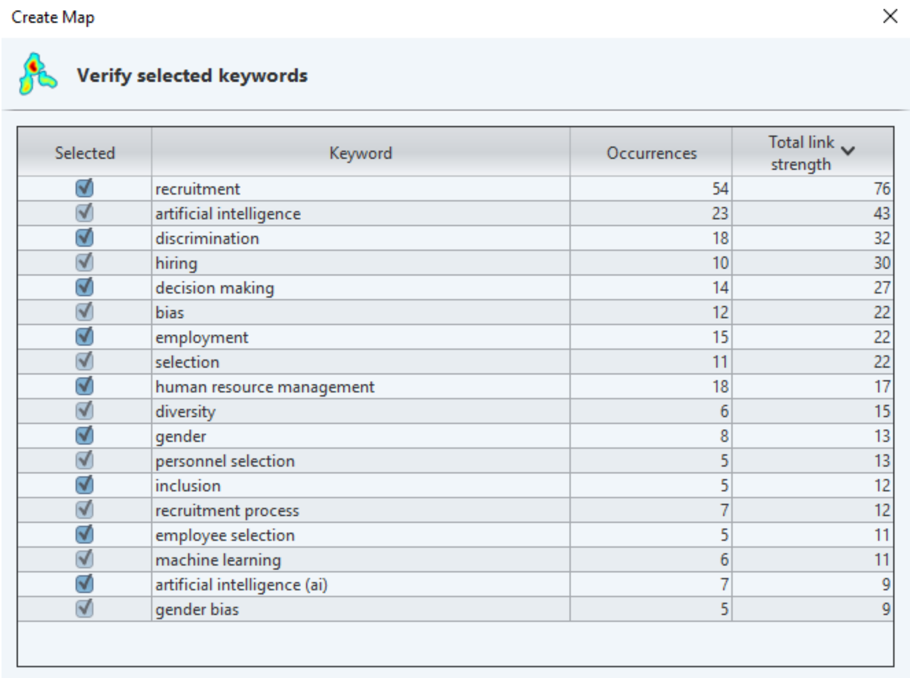
Articles were excluded if they:

1. Not directly related to recruitment (e.g., AI in healthcare or education),
2. Did not address bias or inclusion, or
3. Conference papers, book chapters, or non-peer-reviewed documents.

After applying these criteria and removing duplicates, a total of 92 relevant articles were selected for analysis.

RESULTS

Based on the keyword co-occurrence network generated through bibliometric analysis using VOSviewer, several dominant themes and conceptual relationships can be identified in the literature concerning gender bias and inclusion in Artificial Intelligence (AI)-based recruitment. This visualization provides a structured representation of how scholarly discussions have evolved and how major concepts are interconnected within this research domain.


Create Map

Verify selected keywords

Selected	Keyword	Occurrences	Total link strength
✓	recruitment	54	76
✓	artificial intelligence	23	43
✓	discrimination	18	32
✓	hiring	10	30
✓	decision making	14	27
✓	bias	12	22
✓	employment	15	22
✓	selection	11	22
✓	human resource management	18	17
✓	diversity	6	15
✓	gender	8	13
✓	personnel selection	5	13
✓	inclusion	5	12
✓	recruitment process	7	12
✓	employee selection	5	11
✓	machine learning	6	11
✓	artificial intelligence (ai)	7	9
✓	gender bias	5	9

Figure 2. Keywords Generated by VOSviewer

The analysis shows that "recruitment" is the most frequently occurring keyword, with 54 occurrences and the highest total link strength (76), indicating its central role in the literature. This finding suggests that recruitment remains the primary organizational entry point through which issues of fairness, bias, and inclusion are examined. As recruitment determines access to employment opportunities, it becomes the most critical stage where algorithmic decision-making can either reinforce or reduce structural inequalities.

This result is consistent with Raghavan et al. (2020), who argue that algorithmic hiring systems represent one of the most influential mechanisms through which bias can be institutionalized in organizations. Similarly, Binns (2018) emphasizes that fairness in AI cannot be understood solely through technical optimization but must also be evaluated through ethical and social justice perspectives. The dominance of "recruitment" therefore reflects not only operational importance but also its strategic significance in organizational inclusion.

Other highly connected keywords such as "artificial intelligence," "discrimination," and "human resource management" indicate that the literature increasingly views AI-based recruitment as a socio-technical system rather than merely a technological innovation. This supports Mittelstadt (2016), who explains that algorithmic systems should be understood within broader institutional and social contexts, where human decisions, historical inequalities, and organizational values shape technological outcomes.

The strong presence of "discrimination" and "bias" further confirms that concerns regarding fairness remain central in AI-driven recruitment research. This finding aligns with Barocas & Selbst (2016), who demonstrate that algorithmic systems often reproduce historical inequalities embedded in training data, and with Mehrabi et al. (2021), who identify bias as one of the most persistent challenges in machine learning applications. Thus, the bibliometric results indicate that the discussion surrounding AI in recruitment has shifted from efficiency-oriented implementation toward fairness-oriented evaluation.

Overall, the prominence of these central keywords reflects an important transformation in the literature: AI is no longer discussed only as a tool for improving recruitment efficiency, but also as a critical factor influencing equity, diversity, and workplace inclusion. This shift highlights the growing recognition that technological advancement must be accompanied by ethical governance and inclusive organizational practices.

DISCUSSION

Identification of Research Clusters

The network visualization generated by VOSviewer reveals a strong interconnection among the keywords "recruitment," "artificial intelligence," "bias," "discrimination," "gender," and "inclusion." These relationships indicate that the scholarly discussion on AI-based recruitment is not limited to technological efficiency, but also strongly involves ethical concerns, fairness, and organizational inclusion. Based on the clustering analysis, three major thematic groups can be identified: the Red Cluster (Social and Ethical Issues), the Blue Cluster (Technology and HR Management), and the Green Cluster (Decision-Making and Inclusion).

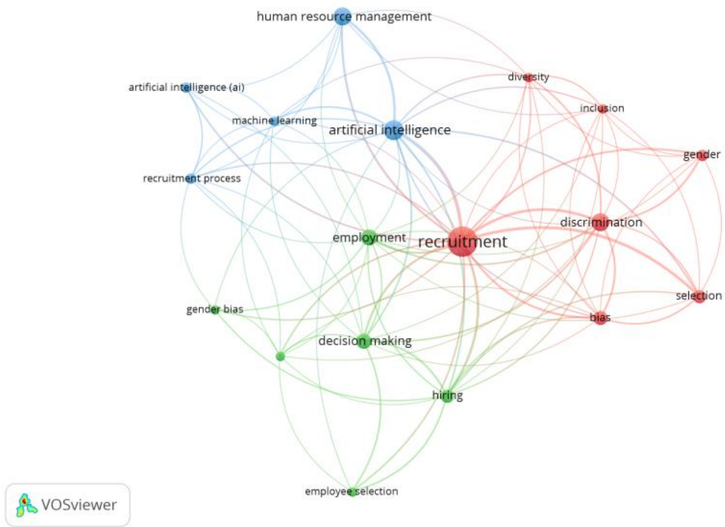


Figure 3. Network Visualization

Red Cluster: Social and Ethical Issues

The red cluster is the most dominant and includes keywords such as "recruitment," "bias," "discrimination," "gender," and "selection." This cluster reflects the growing academic concern regarding fairness in recruitment processes, particularly how gender bias and discrimination emerge when AI systems are applied in candidate screening and selection.

The prominence of this cluster suggests that researchers increasingly recognize that algorithmic recruitment systems are not inherently neutral. Instead, they often inherit patterns of inequality from historical hiring data. This finding strongly supports Barocas & Selbst (2016), who explain that biased historical data can lead to discriminatory algorithmic outcomes, even when the system appears objective. Similarly, Danks & London (2017) argue that algorithmic bias often reflects deeper structural inequalities embedded within organizational decision-making processes.

The presence of the keyword “selection” is particularly significant because it indicates that bias frequently becomes most visible at the final hiring stage, where decisions have direct consequences for employment opportunities. This aligns with Raghavan et al. (2020), who found that algorithmic hiring systems often reinforce institutional inequalities by favoring historically dominant demographic groups. Therefore, this cluster highlights that fairness in recruitment is not only a technical issue, but also a matter of organizational justice and social accountability/

Blue Cluster: Technology and HR Management

The blue cluster is dominated by keywords such as “artificial intelligence,” “machine learning,” “human resource management,” and “recruitment process.” This cluster emphasizes the technological and managerial dimensions of AI implementation in HR functions, particularly how machine learning systems are integrated into recruitment practices.

The strong connection between “artificial intelligence” and “machine learning” confirms that machine learning serves as the core mechanism behind AI-driven recruitment tools, including resume screening, candidate ranking, and predictive hiring models. This Chopal & Garg (2021), who explain that machine learning has become central to modern HR analytics and automated talent acquisition systems.

However, the cluster also reveals that technological adoption cannot be separated from governance challenges. Jobin et al. (2019) emphasize that transparency, accountability, and explainability remain major concerns in AI ethics, particularly when organizations rely on opaque “black-box” systems for hiring decisions. Wachter et al. (2020) further argue that fairness cannot be fully automated, as legal and ethical standards often require contextual human judgment.

Thus, this cluster demonstrates that successful AI adoption in HR management requires more than technical sophistication. It also requires responsible governance, transparent decision-making, and institutional oversight to ensure that efficiency does not compromise fairness.

Green Cluster: Decision-Making and Inclusion

The green cluster includes keywords such as “decision making,” “hiring,” “employee selection,” “gender bias,” and “inclusion.” This cluster focuses on the practical consequences of AI-generated recommendations in organizational hiring decisions and how these decisions shape workplace inclusion outcomes.

The appearance of “inclusion” within this cluster is particularly important because it indicates a shift in research attention from identifying bias toward achieving equitable outcomes. Inclusion here is understood not merely as representation, but as fair access to opportunities and equal participation in organizational processes. This supports Shore et al. (2011), who define inclusion as the degree to which individuals feel valued and able to contribute fully within organizations.

The strong relationship between "gender bias" and "decision making" suggests that recruitment decisions remain highly vulnerable to algorithmically amplified discrimination. Even when AI is designed to improve efficiency, biased recommendations may still influence human hiring managers and shape final decisions. This finding aligns with Binns (2018), who argues that fairness in machine learning must consider institutional consequences rather than only technical performance.

Furthermore, the emergence of inclusion as a visible keyword suggests that recent studies are moving beyond problem identification toward solution-oriented discussions. Researchers are increasingly concerned with how organizations can design fairer systems, conduct algorithmic audits, and establish inclusive HR policies that mitigate discrimination risks.

Interconnections Between Clusters and Central Keywords

The keywords "recruitment" and "employment" function as strong central connectors across all three clusters, indicating that discussions of AI, bias, and inclusion ultimately converge within the broader context of organizational hiring.

The connection between the red and blue clusters shows that bias and discrimination are not separate from AI implementation, but rather direct consequences of how technology is designed and applied. Researchers are therefore shifting from purely technical discussions toward ethical evaluation of AI systems.

Meanwhile, the strong relationship between the red and green clusters highlights that gender bias directly shapes recruitment decisions and inclusion outcomes. This confirms that inclusion cannot be achieved solely through diversity initiatives if bias remains embedded in the recruitment process itself.

Overall, these bibliometric findings demonstrate that gender bias and inclusion in AI-based recruitment should be understood as an integrated socio-technical issue. The literature no longer treats AI as a neutral hiring tool, but as an organizational mechanism capable of both improving efficiency and reproducing inequality. This reinforces the urgency for interdisciplinary approaches that combine technological innovation with ethical governance and inclusive HR practices.

Publication Trends and Evolution of Research Themes

The overlay visualization provides important insights into the temporal development of research themes in AI-based recruitment, particularly regarding gender bias and inclusion. In VOSviewer, node colors represent the average publication year of each keyword, where darker blue or purple nodes indicate earlier research themes, while yellow and green nodes represent more recent and emerging topics.

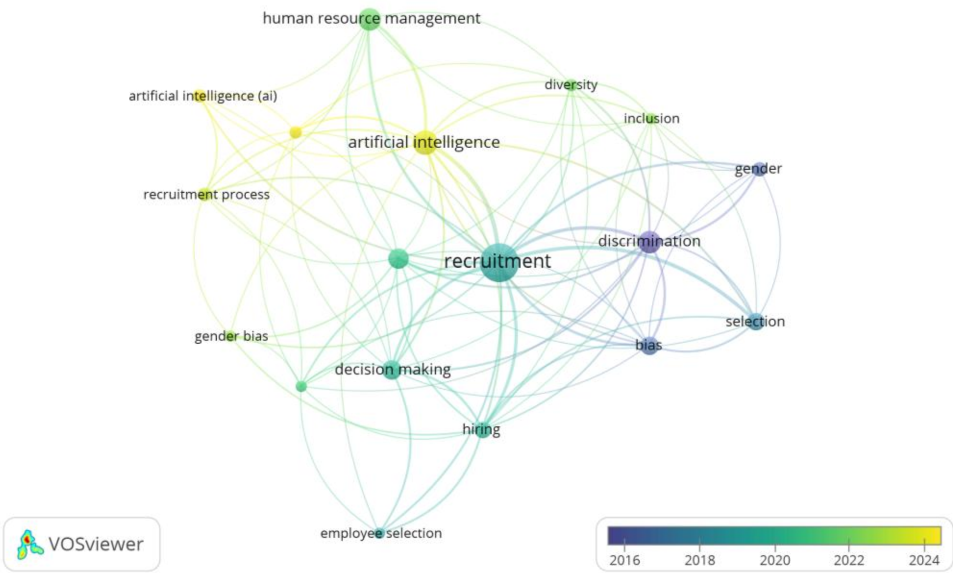


Figure 4. Overlay Visualization

The visualization shows that earlier studies were primarily concentrated on foundational issues such as "gender," "bias," "discrimination," and "selection." These themes reflect the initial academic concern with identifying structural inequalities and discriminatory practices within traditional recruitment systems. Before the widespread adoption of AI in recruitment, discussions mainly focused on human bias, gender inequality, and unequal access to employment opportunities. This finding is consistent with Barocas and Selbst (2016), who explain that historical inequalities in organizational decision-making often become embedded in future technological systems.

In contrast, more recent keywords such as "artificial intelligence," "diversity," and "inclusion" appear in brighter yellow and green colors, indicating a significant shift in scholarly attention toward AI-driven recruitment and its broader ethical implications. This transition reflects the increasing adoption of AI technologies in human resource management and the growing awareness that algorithmic systems can both reduce and reproduce discrimination.

One important factor driving this shift is the expansion of machine learning applications in recruitment, including automated resume screening, predictive candidate matching, and AI-assisted hiring decisions. Chopal & Garg (2021) explain that AI has become a strategic tool in HR management due to its potential to improve efficiency and consistency. However, as organizations increasingly rely on algorithmic systems, concerns regarding fairness, transparency, and accountability have become more prominent.

Another major trigger for this research evolution is the growing public awareness of high-profile algorithmic bias cases, such as the widely discussed Amazon hiring algorithm controversy, where AI systems were found to disadvantage female applicants due to biased historical training data. Cases like this intensified academic and practical debates regarding fairness in AI and strengthened the urgency for responsible AI governance (Jobin et al., 2019; Raghavan et al., 2020).

The emergence of "diversity" and "inclusion" as newer themes also indicates that the literature is moving beyond merely identifying discrimination toward designing fairer and more inclusive recruitment systems. This reflects a broader organizational shift influenced by Diversity, Equity, and Inclusion (DEI) initiatives, ESG considerations, and stronger institutional demands for ethical AI implementation. Inclusion is increasingly positioned not as a secondary HR outcome, but as a strategic objective of recruitment design itself (Nishii, 2013; Shore et al., 2011).

This thematic evolution suggests that the field has progressed through three major stages. The first stage focused on recognizing discrimination and gender inequality in recruitment. The second stage shifted toward examining how AI systems may inherit and amplify these inequalities. The current stage emphasizes responsible AI, algorithmic fairness, and inclusion-centered recruitment strategies.

Despite this progress, the bibliometric results also reveal that studies integrating AI, gender bias, and inclusion within a single conceptual framework remain relatively limited. Much of the literature still examines these issues separately—either focusing on technical AI performance, ethical bias concerns, or diversity outcomes—without sufficiently connecting them. This confirms the research gap identified in this study and highlights the importance of developing more comprehensive socio-technical frameworks.

Therefore, the overlay visualization not only illustrates publication trends but also demonstrates the intellectual maturity of the field. The shift from discrimination-focused research toward inclusion-oriented AI governance reflects a growing recognition that recruitment technology must be evaluated not only by efficiency, but also by its contribution to fairness, equity, and sustainable organizational inclusion.

Density Visualization and Research Concentration

The density visualization provides additional insight into the concentration and intensity of research themes within the literature on gender bias and inclusion in AI-based recruitment. In VOSviewer, areas represented by brighter yellow colors indicate topics with higher research intensity and stronger conceptual connections, while darker green and blue areas represent less frequently discussed or emerging themes.

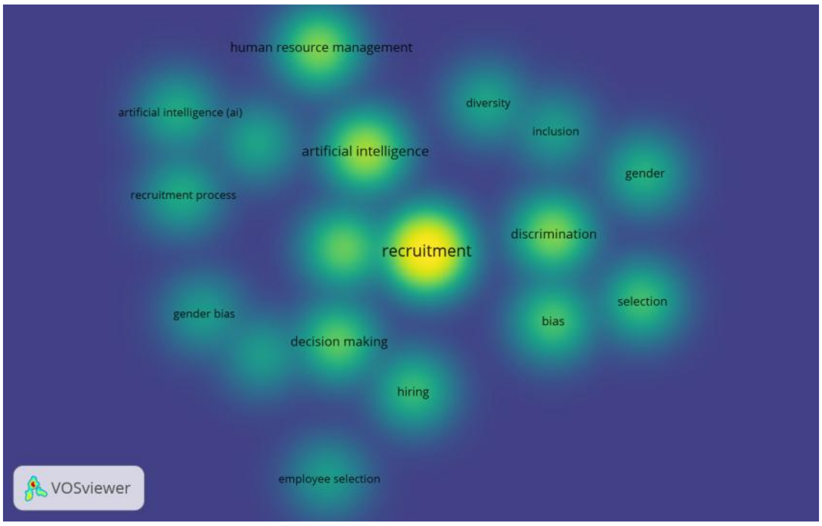


Figure 5. Density Visualization

The visualization shows that the highest density areas are concentrated around keywords such as "recruitment," "artificial intelligence," "bias," "gender," "discrimination," and "human resource management." This confirms that these topics form the intellectual core of the field and continue to dominate scholarly discussions. Their prominence indicates that the academic conversation remains strongly focused on how AI influences recruitment practices and how bias may affect fairness in hiring outcomes.

The concentration around "recruitment" reinforces its role as the central domain where technological innovation and social justice intersect. Recruitment is not only an operational HR function but also the primary gateway to employment opportunities, making it a critical point for inclusion and equality. This finding supports Raghavan et al. (2020), who emphasize that hiring systems are among the most significant institutional mechanisms through which inequality can be reproduced or reduced.

Similarly, the high density of "artificial intelligence" and "machine learning" demonstrates that AI is no longer treated as a supplementary tool, but as a strategic driver of recruitment transformation. Organizations increasingly rely on AI for candidate screening, ranking, and predictive hiring decisions. However, this concentration also reflects growing concern regarding algorithmic fairness, especially when automated systems are used without sufficient transparency or accountability (Jobin et al., 2019; Wachter et al., 2020).

The strong density surrounding "bias," "gender," and "discrimination" indicates that fairness remains one of the most urgent and persistent concerns in the literature. This suggests that despite technological advancement, researchers continue to recognize that AI systems may reinforce existing inequalities rather than eliminate them. This finding aligns with Mehrabi et al. (2021), who identify bias as one of the most difficult challenges in machine learning systems, particularly when historical data reflect long-standing social discrimination.

Interestingly, newer concepts such as "diversity" and "inclusion" appear with lower density compared to traditional themes like bias and discrimination. This indicates that while inclusion is gaining attention, it has not yet become as deeply established in the literature as bias-related discussions. In other words, the field is still stronger in diagnosing problems than in proposing inclusion-centered solutions.

This imbalance reveals an important research gap. Much of the existing literature focuses on identifying bias and fairness issues, but relatively fewer studies examine how organizations can actively design inclusive recruitment systems using AI. Practical strategies such as algorithmic audits, fairness-by-design frameworks, and inclusive HR governance remain underexplored compared to technical discussions of bias detection.

From a theoretical perspective, this density pattern supports the argument that AI-based recruitment should be understood as a socio-technical system rather than a purely technological innovation. As Mittelstadt (2016) explains, algorithmic systems operate within institutional structures shaped by social norms, organizational values, and historical inequalities. Therefore, improving recruitment fairness requires both technical refinement and structural organizational change.

Overall, the density visualization confirms that the literature is highly concentrated around the relationship between AI, recruitment, and bias, while inclusion remains a growing but less developed area of research. This suggests that future studies should move beyond identifying algorithmic discrimination and focus more strongly on designing inclusive recruitment models that ensure equitable access to employment opportunities for diverse candidates.

CONCLUSIONS AND RECOMMENDATIONS

This study systematically mapped the research landscape concerning gender bias and inclusion in Artificial Intelligence (AI)-based recruitment using bibliometric analysis and VOSviewer visualization. The findings reveal that the literature is structured around three major interconnected clusters: social and ethical issues related to gender bias and discrimination, technological dimensions of AI implementation in human resource management, and decision-making processes linked to hiring and workplace inclusion.

The dominance of keywords such as "recruitment," "artificial intelligence," "bias," "gender," and "discrimination" confirms that recruitment remains the central arena where technological efficiency and social justice intersect. While AI is widely adopted to improve speed, consistency, and decision-making quality in hiring, the results demonstrate that algorithmic systems are not inherently neutral. Instead, they may reproduce historical inequalities embedded in training data and organizational practices, particularly gender-based discrimination.

The overlay visualization further shows a significant evolution of research themes. Earlier studies primarily focused on traditional issues of bias, discrimination, and unequal access to employment, while more recent studies increasingly emphasize responsible AI, diversity, and inclusion. This shift indicates that the field has moved from problem identification toward the development of fairer and more inclusive recruitment systems. However, the density visualization also reveals that inclusion remains less established than bias-related discussions, suggesting that the literature is still stronger in diagnosing problems than in proposing practical solutions.

This study also confirms that research integrating AI, gender bias, and inclusion within a single conceptual framework remains relatively limited. Most studies still examine these issues separately, either from technical, ethical, or diversity perspectives, without fully connecting them. This represents an important research gap and supports the need for more comprehensive socio-technical approaches in future studies.

From a practical perspective, organizations should not evaluate AI-based recruitment systems solely based on efficiency and predictive performance. Greater attention must be given to algorithmic audits, transparency of training data, fairness evaluation, and inclusive HR governance. Policymakers and HR practitioners should work collaboratively to ensure that AI implementation supports workplace inclusion rather than reinforcing structural inequality.

FURTHER STUDY

This research has several limitations. First, the analysis was limited to publications indexed in Scopus, which may exclude relevant studies from other databases such as Web of Science or Google Scholar. Second, the co-occurrence analysis depends heavily on author keywords and indexed terms, which may not fully capture all conceptual nuances within the literature. Future studies may expand database coverage, apply citation or co-authorship analysis, and explore comparative perspectives across industries or countries to provide a broader understanding of AI fairness in recruitment.

Despite these limitations, this study contributes by providing a structured overview of the intellectual development of AI-based recruitment research and by proposing a stronger conceptual linkage between technology, gender bias, and inclusion. Ultimately, the future of AI-based recruitment should not be measured solely by technological sophistication, but by its ability to create fairer, more transparent, and genuinely inclusive employment opportunities for all candidates.

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