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Article

Closing the technology-behavioural gap in human resource management: An IPRC framework for mitigating AI bias among Generation Z employees

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Abstract: Artificial intelligence (AI) is increasingly being used in recruitment, employee assessment, workforce analytics, learning recommendations and performance management. Such applications may increase efficiency, but they may also replicate historical inequalities and shape how employees interpret and act on the automated recommendations. This study investigates the application of the Influencers-Processes-Responses-Contextualizers (IPRC) framework in understanding and addressing AI-related bias in the decision-making of the Generation Z workforce. The systematic literature review was supplemented with bibliometric analysis of the research indexed in Scopus. The original Scopus bibliographic export contained 1,712 records; 1,710 records fell within the stated 1990–2025 temporal window, and 224 studies were selected for critical thematic synthesis. VOSviewer was used to map the intellectual structure and thematic development of the field. Included studies were coded within the four IPRC dimensions. The evidence indicates that research is still centred on technical and algorithmic processes, but behavioural responses, organisational conditions and evidence specific to the Generation Z workforce are less developed. The adapted framework suggests that biased outcomes occur through complex interactions between influential information sources, data and model design, human cognitive processing, employee responses, and contextual factors, such as HR policy, organizational culture, AI literacy and regulation. For HRM practice, technical audits must be combined with transparent decision protocols, meaningful human oversight, employee capability development, feedback and appeal mechanisms, and continuous monitoring of unequal outcomes. The study recasts AI bias as a socio-technical HRM challenge and puts forward an integrative research agenda for responsible human–AI workforce decision-making.

Keywords: Artificial Intelligence (AI), Bias Mitigation, IPRC Framework (Influencer–Process–Response–Contextualization), Generation Z

1. Introduction

Artificial Intelligence is increasingly being integrated into human resource management (HRM) in the form of algorithmic recruitment, employee profiling, workforce analytics, learning recommendations, performance evaluation and decision support . They may enhance the speed and consistency of processing, but they can also reproduce inequalities embedded in historical data, organizational routines, and model-design choices (Bouzerda et al., 2025; Ferrara, 2024; Tariq, 2025). So AI bias isn't just a technical defect. This is an HRM problem because managers and employees interpret, accept, contest or act upon AI-generated recommendations within consequential employment decisions.

The organizational consequences of biased AI extend beyond statistical accuracy. Automated systems can disadvantage particular groups during hiring, reinforce narrow definitions of talent, influence access to development

opportunities and weaken employee trust when decisions are opaque or difficult to challenge (Harris, 2024; Nadeem et al., 2022; Trad, 2025). At the same time, human judgment is not neutral: confirmation bias, anchoring, stereotyping and automation bias may affect how AI systems are designed and how their outputs are interpreted (Fasolo et al., 2025; Gilbert & Mintz, 2019; Nishant et al., 2024). Responsible HRM must consequently address the interaction between algorithmic and human sources of bias.

Generation Z is especially relevant as an increasing proportion of this cohort enters the workforce while using algorithmic platforms and generative AI in education, job search, communication and work. But digital familiarity is not the same as algorithmic literacy. The frequent use of AI can be coupled with limited understanding of data provenance, model uncertainty, persuasive design and automated discrimination. Research with students and pre-service professionals demonstrates that technological competence depends on institutional support, practice-based learning, and policy guidance, rather than merely exposure (Lu & Said, 2025; Wang & Ding, 2024). Thus, Generation Z should be conceptualised as a heterogeneous workforce context that needs to be empirically examined, not as a homogeneous category of technology-competent workers.

Technical research concentrates on datasets, model architectures, fairness metrics and debiasing methods; behavioural research examines trust, cognitive bias and reliance; and HRM research focuses on recruitment automation, people analytics and digital capability development (Calegari et al., 2023; Korteling et al., 2021; Srinivasan & Chander, 2021). What is missing is an integrative framework that explains how sources of influence, algorithmic and cognitive processes, employee responses and organizational conditions jointly shape AI-supported workforce decisions.

This study addresses that gap by adapting the Influencers–Processes–Responses–Contextualizers (IPRC) framework. The framework is derived from digital-influence research, where outcomes are explained through the interaction of influential sources, persuasion processes, audience responses and contextual conditions (de Brito Silva et al., 2025; Pan et al., 2025; Pushparaj & Kushwaha, 2024). Its application to AI bias is a theoretical extension rather than the use of an already validated AI-governance model. IPRC is used here as an organizing lens that complements, rather than replaces, technical fairness and responsible-AI approaches.

The study addresses three questions: (RQ1) What intellectual and thematic structures characterize research on AI bias, human decision-making and organizational governance? (RQ2) How can the IPRC dimensions explain the emergence and remediation of AI bias in Generation Z workforce decision-making? (RQ3) What theoretical, methodological and practical implications does the adapted framework offer for responsible HRM?

The study contributes in three ways. First, it reframes AI bias for HRM readership by connecting responsible AI with recruitment, performance management, employee development, engagement and employee voice. Second, it clarifies the conceptual transfer of IPRC from digital-influence research to a socio-technical workforce context. Third, it integrates bibliometric mapping with critical thematic synthesis to identify where technical progress has outpaced behavioural, organizational and Generation Z-specific evidence.

2. Literature Review

2.1. AI Bias as a Socio-Technical HRM Problem

AI systems can generate unequal outcomes through biased training data, proxy variables, class imbalance, feature selection, decision thresholds and opaque model architectures (Ferrara, 2024; Majumdar et al., 2024; Nadeem et al., 2022;

Sinha et al., 2024). These technical mechanisms are consequential in HRM because employment data frequently reflect prior organizational decisions. A model trained on historically unequal hiring or promotion records may reproduce those patterns while presenting them as neutral predictions.

Bias also emerges through human and institutional processes. Developers determine which outcomes are optimized, managers decide when to rely on automated recommendations, and employees interpret AI outputs through existing expectations and cognitive shortcuts (Irshad, 2024; Nishant et al., 2024). Organizational culture, resource priorities and regulatory incentives influence whether fairness is addressed early or postponed as a form of 'fairness debt' (Aryan et al., 2025; Ulnicane & Aden, 2023). Consequently, technical performance cannot by itself establish that an AI-supported HR decision is fair, legitimate or appropriate.

Bias mitigation therefore requires a socio-technical approach. Fairness-aware learning, data reweighting and model auditing can reduce measurable disparities, while human-in-the-loop review, explainability and contestability can improve accountability in high-stakes decisions (Calegari et al., 2023; Choi et al., 2025; Harris, 2024; Waller et al., 2024). These measures are effective only when embedded in governance arrangements that define responsibility, provide employee voice and support continuous monitoring.

For HRM, the central issue is not whether AI should replace or assist human decision-makers, but how authority and accountability are distributed across the decision system. Responsible use requires clarity about when AI advice is advisory, when human review is mandatory, how affected employees can challenge outcomes, and how organizations learn from errors. This shifts attention from isolated algorithmic correction toward the design of responsible human–AI decision processes.

2.2. Theoretical Adaptation of the IPRC Framework

In digital-influence research, outcomes are shaped by the characteristics of influential sources, the mechanisms through which messages are processed, audience responses and the surrounding social or platform context (de Brito Silva et al., 2025; Kim et al., 2021; Sundermann & Munnukka, 2022). This structure is useful for AI-supported HR decisions because an AI output is never interpreted in isolation. Its influence depends on who or what presents it, how it is generated and explained, how the user responds, and the organizational context in which the decision occurs.

The Influencers dimension includes AI-generated recommendations, managers, peers, vendors, training data and interface cues that affect perceived authority or credibility. In recruitment, for example, a ranking may be accepted because it is presented as objective or endorsed by senior management. The Processes dimension includes the technical pipeline and the cognitive interpretation of the output. It therefore covers data preparation, model design, explainability, anchoring, confirmation bias and human–AI interaction.

The Responses dimension captures trust, reliance, resistance, compliance, contestation and subsequent decision quality. This dimension expands the original focus on immediate consumer behaviour to include perceived fairness, employee acceptance and the willingness to question automated recommendations (Bouzerda et al., 2025). The Contextualizers dimension includes HR policy, organizational culture, job characteristics, power relations, regulation, demographic conditions and AI literacy. These contextual conditions determine whether users have the knowledge and authority to challenge an AI-supported decision. The adaptation of the four IPRC dimensions to AI-supported HRM decisions is summarized in **Table 1**.

This adaptation does not imply that IPRC has already been empirically validated for AI bias. Its value is integrative: it connects technical mechanisms with behavioural and organizational processes that are often treated separately. Empirical testing is therefore a central future requirement, particularly across different HR functions, occupations, cultures and levels of AI exposure.

Table 1. Mapping the IPRC Framework to AI-Supported HRM Decisions

IPRC dimension	Meaning in AI-supported HRM	Generation Z/workforce risk	HRM remediation
Influencers	AI recommendations, managers, peers, vendors, training data and interface cues.	Authority bias, social conformity and uncritical trust in apparently objective outputs.	Disclose AI use; clarify decision authority; use diverse review panels and vendor due diligence.
Processes	Data preparation, model design, cognitive interpretation and human–AI interaction.	Automation bias, anchoring, confirmation bias and limited understanding of model logic.	Conduct bias audits; use explainability, structured review criteria and human-in-the-loop checks.
Responses	Trust, reliance, resistance, compliance, contestation and feedback.	Overreliance, disengagement, inappropriate rejection or inability to challenge outcomes.	Develop AI literacy; provide feedback and appeal channels; monitor calibrated trust.
Contextualizers	HR policy, culture, job design, power relations, regulation and AI literacy.	Unequal effects across jobs and employee groups; weak employee voice.	Use impact assessments, participatory governance, continuous monitoring and role-based training.

2.3. Generation Z as an Emerging Workforce Context

The Generation Z focus requires more than repeated references to age or digital nativeness. Much of the reviewed literature relies on student or young-adult samples, yet rarely tests whether the observed mechanisms are unique to Generation Z. The current evidence therefore supports a workforce-focused research agenda, but not a deterministic generational profile. Three characteristics warrant examination. First, frequent exposure to recommendation systems and generative AI may normalize automated guidance and increase the risk of overreliance. Second, platform-based social comparison and information overload may affect trust, fatigue and critical evaluation (Wang & Ding, 2024). Third, early-career employees may have limited organizational power to question automated screening, monitoring or performance decisions. These mechanisms should be tested rather than assumed. From an HRD perspective, AI literacy should include more than operational competence. Employees need to understand data limitations, uncertainty, bias, privacy, explainability and their right to request human review. Institutional support, practical experience and policy guidance are important conditions for developing such competence (Lu & Said, 2025).

2.4. An IPRC-Based Bias-Remediation Pathway

An IPRC-based remediation pathway begins by identifying the influential sources that shape acceptance of AI outputs, including managerial endorsement, vendor claims and interface design. The next step is to examine both technical and cognitive processes: data representativeness, model objectives, explainability, anchoring and confirmation bias. Organizations then assess employee and managerial responses, including trust, reliance, resistance and the use of appeal mechanisms. Finally, the decision is evaluated within its organizational and regulatory context.

The pathway is iterative rather than linear. Employee feedback and outcome monitoring should recalibrate data, models, decision rules and training interventions. Internal controls, algorithm audits and governance committees can support this feedback cycle, but they must be linked to clear ownership and escalation procedures (Bouzerda et al., 2025; Huang, 2025). In practice, the framework suggests a layered remediation strategy: technical safeguards to detect

and reduce disparities; behavioural safeguards to slow uncritical acceptance; capability development to strengthen AI literacy; procedural safeguards to ensure explanation and human review; and contextual governance to monitor outcomes across employee groups. The intended outcome is not bias-free automation, which may be unrealistic, but a decision system in which bias can be detected, challenged and corrected.

Building on the above discussion, **Figure 1** shows the IPRC framework translated into a bias repair pathway, with a focus on HRM. The model suggests that the AI-augmented workforce outcomes are sequentially influenced by factors (e.g., AI suggestions, managerial input, peer interactions, and platform signals), processes (e.g., data and model architecture, cognitive analysis, and human–AI engagement), and reactions (e.g., trust, dependence, opposition, challenge, and decision-making efficacy). These relationships are embedded in broader contextual factors, including HR policies, company culture, work design, regulations, power relations, and AI literacy. The HRM results of equity, clarity, employee empowerment, and wise decision-making are not viewed as ultimate endpoints but as ingredients for ongoing feedback and adjustment. This underscores the view that tackling AI bias in human resource management is an ongoing socio-technical governance process, rather than a one-time technical fix.

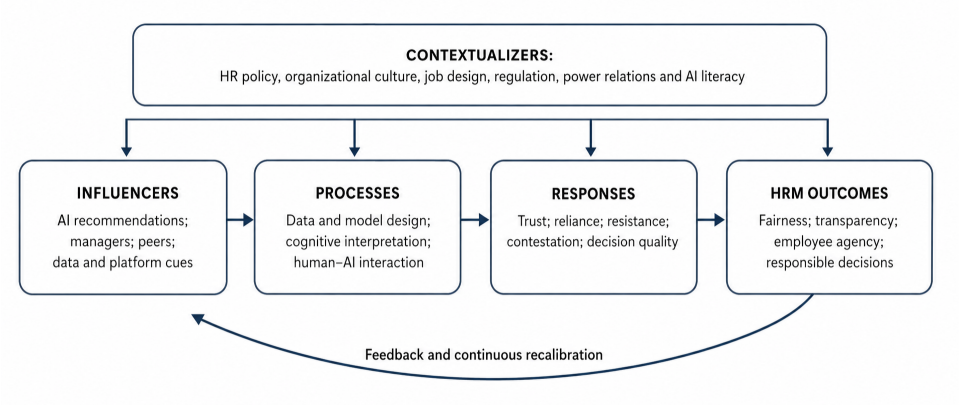


Figure 1. Adapted IPRC pathway for responsible AI-supported HRM decisions.

3. Methodology

3.1. Review Design and Data Sources

The present study integrated a systematic literature review and bibliometric analysis. The methods had complementary purposes. Bibliometric analysis delineated the intellectual structure and temporal evolution of the literature, and a systematic review provided critical interpretation and thematic synthesis guided by IPRC. The separation of the two datasets and analytical purposes allows for greater methodological transparency and avoids taking descriptive network maps as direct evidence of the framework.

Scopus was the sole database used for the systematic search and served as the source of all records considered for screening and analysis. Scopus was selected because of its multidisciplinary coverage of management, social science, decision science and computer science. ScienceDirect was not searched as an additional or independent database. It was consulted only to obtain the full text of documents that had already been identified through the Scopus search when the full text was not otherwise accessible.

3.2. Search Strategy and Dataset Construction

The extensive Scopus query combined AI terms with bias and fairness terms: TITLE-ABS-KEY (“artificial intelligence” OR “machine learning” OR “deep learning” OR “AI”) AND TITLE-ABS-KEY (“bias mitigation” OR “algorithmic

bias" OR "fairness" OR "discrimination"). Database filters were applied for subject area, document type, source type, language and final publication stage. The term IPRC was deliberately excluded from the original search query because the retrieval stage was designed to capture the broader AI-bias and fairness literature without presupposing the IPRC framework. IPRC was applied only after literature retrieval and eligibility screening as a post-hoc analytical lens. The 224 included studies were subsequently interpreted and coded according to the four IPRC dimensions—Influencers, Processes, Responses and Contextualizers—with studies permitted to contribute to more than one dimension where relevant. This approach broadens conceptual coverage while requiring transparent coding, and it is therefore acknowledged as a methodological limitation.

The broad Scopus search yielded 28,024 records. After database filters were applied, 1,712 final English-language articles were exported as the original bibliographic dataset. A temporal consistency check identified two metadata records outside the stated 1990–2025 analytical period. The archived export therefore remained at 1,712 records and was used for non-temporal bibliometric network mapping, whereas analyses explicitly bounded to 1990–2025, including publication-year summaries, used the 1,710 records that fell within the specified time window. After title, abstract and full-text screening, 224 studies were included for IPRC-guided thematic synthesis. The remaining 1,486 records were excluded because they lacked a substantive AI-bias or fairness focus, were not behaviorally or organizationally relevant, were purely technical with no implications for human decision-making, or did not provide sufficient full-text relevance.

3.3. Eligibility and Reporting-Quality Assessment

Refinement of eligibility criteria for better replicability. Peer-reviewed English-language articles covering AI or machine-learning bias, fairness, discrimination or bias mitigation and offering behavioral, organizational, workforce, governance or decision-making relevance were included. Studies could be empirical, conceptual or review studies. We excluded editorials and abstracts and non-peer-reviewed items; studies with no substantive AI component; studies with purely technical performance, but no fairness or human decision relevance; and publications for which we could not obtain sufficient evidence from the full text to code. The complete inclusion and exclusion criteria are presented in **Table 2**.

During full-text assessment, each study was screened for four reporting-quality criteria: clarity of research purpose, identifiable method or conceptual procedure, traceable findings or propositions, and direct relevance to at least one review question. No single numerical risk-of-bias score was imposed due to the heterogeneous nature of the corpus in terms of technical, behavioral and conceptual designs. This decision increases inclusiveness, but decreases the possibility of direct comparison of methodological quality between studies.

Table 2. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
1. Peer-reviewed English-language journal article	1. Editorial, abstract, or non-peer-reviewed item
2. AI or machine-learning focus	2. No substantive AI component
3. Substantive attention to bias, fairness, discrimination, or mitigation	3. No bias or fairness relevance
4. Behavioural, organizational, workforce, governance, or decision-making relevance	4. Purely technical performance study without human or organizational implications
5. Sufficient full-text evidence for coding	5. Insufficient full-text relevance or reporting detail

3.4. Bibliometric and Thematic Analysis

For bibliometric analysis, the archived Scopus export comprised 1,712 records and was used in VOSviewer for non-temporal keyword co-occurrence and network mapping. For temporal analyses explicitly restricted to 1990–2025, the two out-of-range metadata records were excluded, leaving 1,710 records. Accordingly, 1,712 refers to the original bibliographic export and non-temporal mapping dataset, whereas 1,710 refers to the time-bounded analytical subset. A structured extraction matrix was used to examine the 224 included studies, capturing research setting, method, AI application, bias type, population, principal findings, HRM relevance and alignment with the four IPRC dimensions. The IPRC coding was conducted after retrieval and eligibility screening; the included studies were interpreted across Influencers, Processes, Responses and Contextualizers and then synthesized critically by comparing convergence, contradiction and missing evidence across dimensions. The review used bibliographic data and published research available in the public domain and did not involve human participants or animals. The bibliographic export, screening log and 224-study coding matrix should be retained as supplementary or auditable materials for editorial verification. The overall screening and analytical procedure is summarized in **Figure 2**.

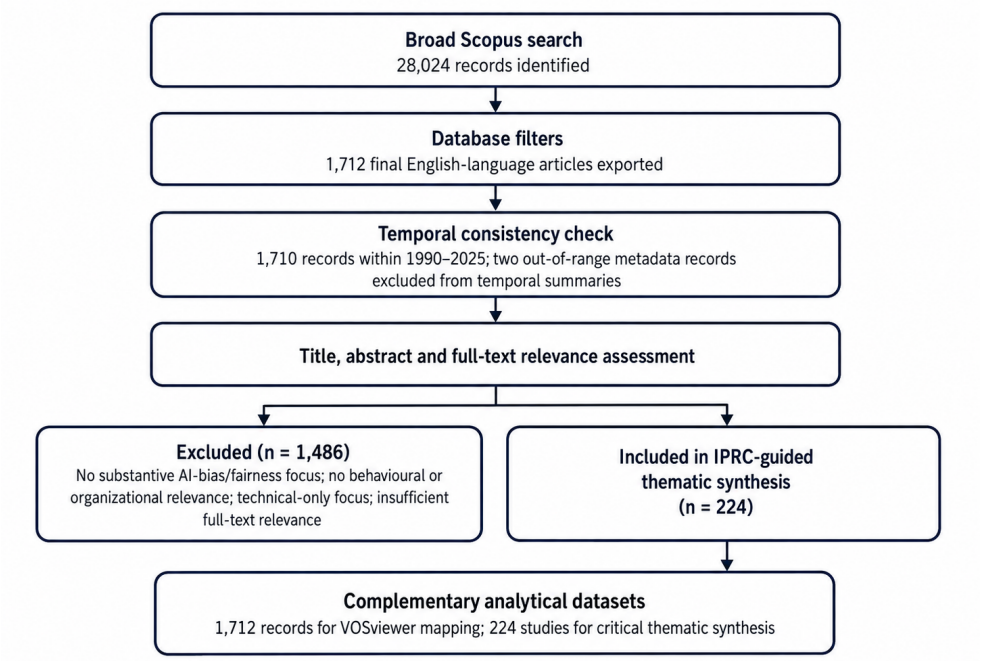


Figure 2. PRISMA-informed dataset construction and analytical separation.

4. Result and Discussion

4.1. Publication Profile and the Technology–Behavioural Imbalance

The original bibliometric export contained 1,712 final English-language articles. Of these, 1,710 records fell within the stated 1990–2025 analytical window and were used for publication-year summaries, while the archived 1,712-record export was retained for non-temporal network mapping. Within the 1990–2025 subset, publication output accelerated after 2017 and increased sharply from 60 articles in 2019 to 448 in 2024, followed by 330 articles in 2025. This pattern confirms the rapid expansion of AI-bias research, but publication volume alone does not demonstrate equivalent progress in behavioural or HRM understanding.

The evidence base was technologically weighted. The network maps were dominated by terms associated with artificial intelligence, machine learning,

fairness, algorithmic bias, classification and deep learning. Human, psychological, educational and organizational terms were present but less central. This imbalance supports the study's technology–behavioural gap: technical mitigation has advanced faster than research on user interpretation, employee response and organizational implementation.

4.2. Network Structure of the Literature

Figure 3 displays the keyword co-occurrence network. Four broad knowledge domains can be interpreted: algorithmic fairness and governance; machine-learning design and classification; human and psychological consequences; and education, literacy and application contexts. These clusters do not empirically validate the IPRC framework. Instead, they identify conceptually related domains that were subsequently integrated through the thematic synthesis.

The map also shows that fairness and algorithmic bias connect technical and human-oriented topics. This bridging position is important for HRM because workforce decisions are produced through both model design and organizational interpretation. A technically fair model may still be used unfairly, while a carefully governed process may reduce harm even when model uncertainty remains.

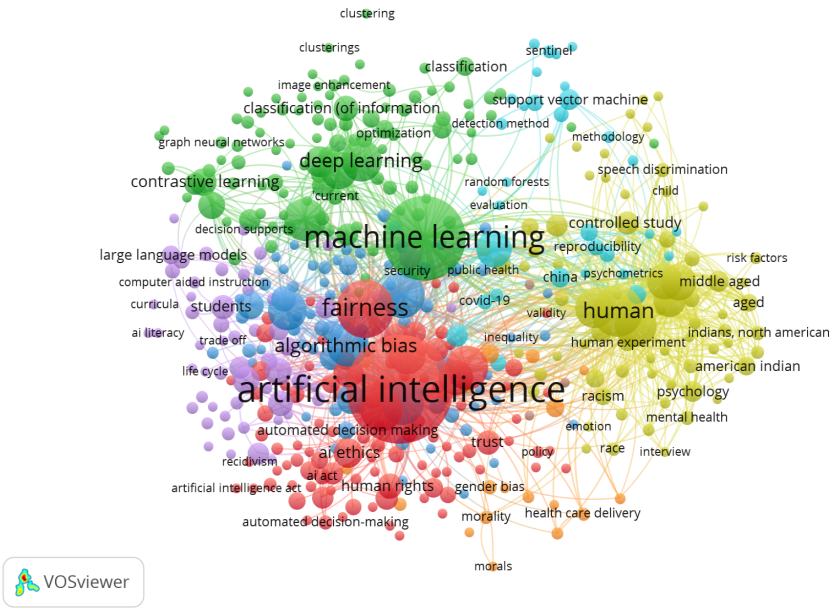


Figure 3. Network Visualization in VOSviewer

4.3. Temporal Evolution of Research Themes

The overlay visualization in **Figure 4** indicates that more recent topics include large language models, students, AI literacy and emerging forms of automated decision-making. Earlier work was more strongly associated with established machine-learning, classification, human-subject and fairness research. The shift suggests growing attention to how rapidly diffusing AI tools are encountered by learners and future employees.

For Generation Z, the overlay evidence is suggestive rather than conclusive. The appearance of student and AI-literacy terms indicates increasing relevance, but the map does not establish generation-specific susceptibility or remediation. This distinction is important because bibliometric proximity cannot substitute for direct empirical comparison of generational groups.

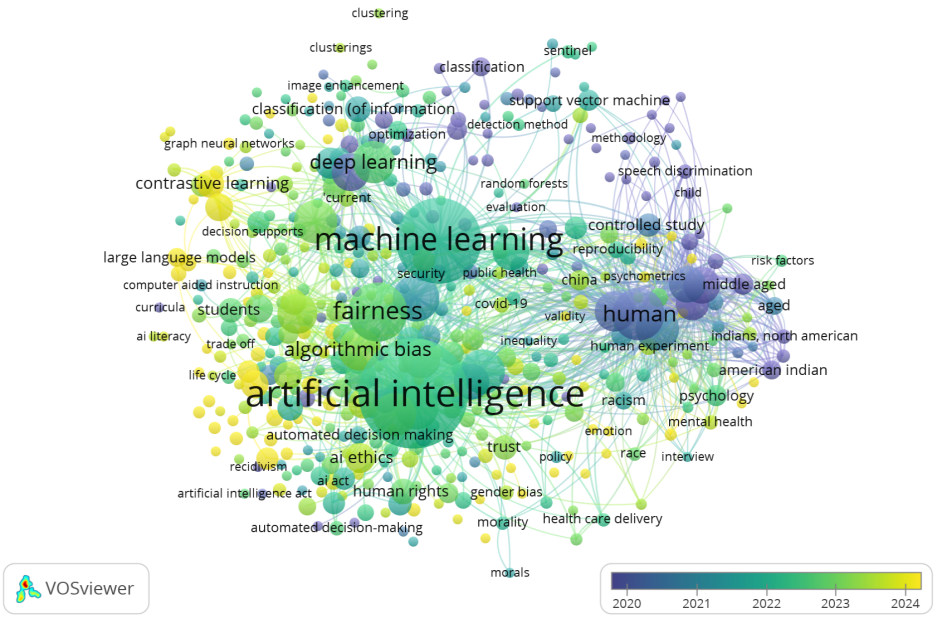


Figure 4. Overlay Visualization in VOSviewer

4.4. IPRC-Based Critical Synthesis

Influencers. The review indicates that AI recommendations acquire influence through claims of objectivity, managerial endorsement, interface design and the credibility of the source. Digital-influence research shows that perceived credibility and relational cues affect acceptance, while HRM research demonstrates that human capability and organizational authority shape how algorithmic recommendations are interpreted (de Brito Silva et al., 2025; Trad, 2025). For Generation Z employees, future research should distinguish trust in the technology from compliance caused by hierarchy or lack of decision-making authority.

Processes. The strongest evidence concerns the process dimension. Bias can enter through unrepresentative data, proxy variables, model architecture, feature selection and performance thresholds, and can be amplified through anchoring, confirmation bias or uncritical reliance (Majumdar et al., 2024; Nishant et al., 2024; Sinha et al., 2024). The key gap is that technical and cognitive processes are usually studied separately. Integrated studies are needed to test whether explanations, human review and debiasing prompts improve both fairness and decision quality.

Responses. User responses determine whether AI bias is reproduced, challenged or corrected. Trust can support adoption, but excessive trust can create automation bias; resistance can protect autonomy, but indiscriminate rejection may also reduce decision quality. HRM research should therefore measure perceived fairness, calibrated trust, reliance, resistance, appeal behaviour, and the quality of final decisions rather than treating adoption intention as the only response (Bouzerda et al., 2025; Korteling et al., 2021).

Contextualizers. Organizational policies, culture, job characteristics, national regulation, employee power and AI literacy determine whether remediation mechanisms are usable in practice. A formal appeal channel has little value when employees fear retaliation or do not understand that AI was involved. Likewise, algorithm audits are insufficient when findings are not linked to accountability and corrective action. The Contextualizers dimension therefore connects bias mitigation with governance and human resource development (Lu & Said, 2025; Ulnicane & Aden, 2023). **Table 3** synthesizes the principal findings, research

gaps and proposed HRM interventions across the four IPRC dimensions.

Table 3. Critical Synthesis of IPRC Findings, Gaps and HRM Interventions

Dimension	Main Finding	Critical GAP	HRMIntervention
Influencers	AI outputs, managers, peers, vendor claims, training data and interface cues shape perceived authority.	Limited evidence on how early-career employees evaluate competing human and algorithmic sources.	Disclose AI use; clarify decision authority; use diverse review panels; assess vendor claims.
Processes	Bias enters through data, model objectives and human cognitive interpretation, including anchoring and automation bias.	Technical and cognitive processes are rarely examined in one study.	Combine data/model audits with structured human review, explainability and reflective decision protocols.
Responses	Trust, reliance, resistance, perceived fairness, contestation and feedback determine whether bias is amplified or corrected.	Employee voice, appeal behaviour and long-term trust are under-researched.	Provide explanation, feedback and appeal channels; monitor overreliance and inappropriate rejection.
Contextualizers	HR policy, organizational culture, job design, regulation, power relations and AI literacy shape outcomes.	Cross-cultural, occupational and organizational comparisons remain limited.	Use impact assessments, governance committees, role-based AI training and continuous subgroup monitoring.

4.5. Implications for Human Resource Management Practice

Recruitment and selection. Organizations should validate whether screening tools produce unequal outcomes, document the role of AI in shortlisting, require human review for adverse decisions and provide candidates with an appropriate channel for explanation or reconsideration. Hiring managers should be trained to avoid treating algorithmic rankings as objective facts (Harris, 2024; Tariq, 2025).

Performance management and people analytics. AI-supported performance systems should use job-relevant indicators, test for subgroup disparities and separate developmental feedback from punitive monitoring. Employees should know what data are used, how recommendations are generated and who remains accountable for the final judgment.

Learning and development. AI literacy should be treated as a workforce capability that combines technical use, critical evaluation, ethical awareness and knowledge of employee rights. Scenario-based exercises can help Generation Z employees practice when to use, question or escalate AI advice (Lu & Said, 2025).

Employee engagement and voice. Responsible AI governance requires employee participation. Feedback channels, appeals, multidisciplinary governance committees and periodic impact reviews can convert employee experience into model and process improvement. These mechanisms also reduce the risk that bias remediation remains a specialist technical activity disconnected from everyday HR practice.

4.6. Research Gaps and Future Agenda

Besides, two leading positions required to enhance theoretical clarity, empirical rigor and practical relevance in eliminating bias of artificial intelligence with the help of IPRC exploration need to be investigated. It enables a comprehensive assessment relevant to the literature that had been developed by D. Anthony Miles (2017): Seven –Gap identification to research This perspective highlighted target assignment, behavioral measurement, methodological variation, and contextual applicability challenges with a focus on the integration of theory.

The review identifies a set of connected gaps rather than isolated deficiencies. The central theoretical gap is the absence of a validated model that connects technical bias, human cognition, employee response and organizational context. The methodological gap is the limited use of designs capable of observing these mechanisms over time and in real organizational decisions. The Generation Z gap

is especially important: the literature frequently invokes digital nativeness but rarely conducts direct cohort or career-stage comparisons. The reported research gap identified in the literature for this work is presented in **Table 4** below.

Table 4. Research Agenda for IPRC-Based AI-Bias Remediation in HRM

Gap	Current limitation	Priority research direction
Theoretical	IPRC has not been validated as an AI-bias framework.	Test relationships among the four dimensions and compare IPRC with existing responsible-AI and behavioural models.
Generation Z	Evidence is often based on students or young adults without generational comparison.	Use age, career-stage and cohort comparisons; avoid treating Generation Z as homogeneous.
HRM coverage	Recruitment receives more attention than development, performance, engagement and employee relations.	Examine AI bias across the full employee lifecycle.
Methodological	Cross-sectional, descriptive and technically isolated designs dominate.	Use experiments, field studies, longitudinal designs, mixed methods and algorithm audits.
Measurement	Few validated measures capture calibrated trust, automation bias, contestability and AI literacy.	Develop and cross-validate context-sensitive behavioural and HRM instruments.
Context	Organizational culture, power, job design and regulation are insufficiently integrated.	Conduct multi-level and cross-cultural studies across occupations and levels of AI exposure.
Practice	Technical correction is often separated from employee participation and governance.	Evaluate combined interventions involving audits, training, human oversight, feedback and appeals.

5. Conclusion

This review reframes AI bias as a socio-technical HRM challenge. Biased workforce outcomes do not arise only from data or algorithms; they emerge through interactions among influential sources, technical and cognitive processes, employee responses and organizational conditions. The adapted IPRC framework brings these elements together and provides a structured pathway for examining how bias is produced, accepted, challenged and corrected.

The principal practical implication is that technical audits are necessary but insufficient. Responsible AI-supported HRM also requires transparent decision protocols, meaningful human oversight, AI-literacy development, employee feedback and appeal mechanisms, and continuous monitoring of unequal outcomes. These safeguards are especially relevant to Generation Z employees, but the review cautions against assuming that digital familiarity automatically produces critical AI competence.

The framework remains a conceptual extension rather than an empirically validated theory of AI-bias remediation. The review is also limited by its reliance on Scopus, the breadth of the original search, heterogeneous study designs and incomplete generation-specific evidence. In addition, the supplied bibliographic export contained two records outside the stated analytical period, underscoring the need to archive and verify the final search and screening files.

Future research should test the IPRC relationships through experiments, longitudinal studies, mixed methods and organizational field research across recruitment, learning, performance management, employee engagement and people analytics. The broader goal is not to portray AI as either objective or inherently harmful, but to design human–AI decision systems in which fairness, employee agency and organizational accountability are jointly protected.

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Ramantoko and Refi Rifaldi Windya Giri; writing—original draft preparation, Ihsan Hadiansah; writing—review and editing, Indrawati, Gadang Ramantoko and Tri Widarmanti; visualization, Refi Rifaldi Windya Giri; supervision, Indrawati; project administration, Tri Widarmanti; funding acquisition, Indrawati.

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