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ARTIFICIAL INTELLIGENCE IN DIGITAL RECRUITMENT: SYSTEMATIC REVIEW OF TOOLS, METHODS, AND RESULTS, 2015–2025 TRENDS

INTELIGENCIA ARTIFICIAL EN RECLUTAMIENTO DIGITAL: REVISIÓN SISTEMÁTICA DE HERRAMIENTAS, MÉTODOS Y RESULTADOS, TENDENCIAS 2015–2025

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ABSTRACT:

This systematic review analyzes the implementation of artificial intelligence in digital recruitment processes through a comprehensive examination of scientific articles published over the last decade. Following PRISMA guidelines, databases such as Scopus, ScienceDirect, and Sage Publications were consulted to identify tools, methods, and outcomes of artificial intelligence adoption in talent acquisition. Results reveal that machine learning algorithms for CV screening are among the most widely used tools, followed by conversational artificial intelligence systems and predictive personality analysis. While most studies reported improvements in operational efficiency, including reductions in screening time, fewer studies documented improvements in candidate diversity, indicating a critical tension between technical optimization and social equity. Methodological approaches predominantly employed controlled experimental studies focused on technical metrics rather than social impact indicators. Ethical concerns persist, with documented gender and racial biases in automated screening systems. Furthermore, only a limited proportion of studies, explicitly addressed Sustainable Development Goals related to decent work, innovation and infrastructure, revealing a disconnection between technological innovation and sustainability frameworks. These findings highlight the need for integrative governance frameworks that balance operational efficiency with ethical responsibility, incorporating human oversight, procedural transparency, and accountability mechanisms to ensure that artificial intelligence deployment aligns with principles of sustainable development and social justice in the era of digital transformation.

Keywords: Artificial intelligence, Digital transformation, Recruitment, Development goals, Human resource management, Innovation system.

RESUMEN:

Esta revisión sistemática analiza la implementación de la inteligencia artificial en los procesos de reclutamiento digital mediante un examen integral de artículos científicos publicados durante la última década. Siguiendo las directrices PRISMA, se consultaron bases de datos como Scopus, ScienceDirect y Sage Publications para identificar herramientas, métodos y resultados de la adopción de la inteligencia artificial en la gestión del talento. Los resultados revelan que los algoritmos de aprendizaje automático para la selección de currículos se encuentran entre las herramientas más utilizadas, seguidos por los sistemas de inteligencia artificial conversacional y el análisis predictivo de personalidad. Aunque la mayoría de los estudios reportan mejoras en la eficiencia operativa, incluyendo reducciones en el tiempo de selección, menos investigaciones documentan mejoras en la diversidad de candidatos, lo que evidencia una tensión crítica entre la optimización técnica y la equidad social. Los enfoques metodológicos se basan principalmente en estudios experimentales controlados centrados en métricas técnicas, más que en indicadores de impacto social. Persisten preocupaciones éticas, con sesgos de género y raza documentados en sistemas automatizados de selección. Además, solo una proporción limitada de estudios aborda explícitamente los Objetivos de Desarrollo Sostenible relacionados con trabajo decente, innovación e infraestructura, lo que revela una desconexión entre la innovación tecnológica y los marcos de sostenibilidad. Estos hallazgos destacan la necesidad de marcos de gobernanza integradores que equilibren la eficiencia operativa con la responsabilidad ética, incorporando supervisión humana, transparencia procedimental y mecanismos de rendición de cuentas para garantizar que la implementación de la inteligencia artificial se alinee con los principios del desarrollo sostenible y la justicia social en la era de la transformación digital.

Palabras clave: Inteligencia artificial, Transformación digital, Reclutamiento, Objetivos de Desarrollo, Gestión de recursos humanos, Sistema de innovación.

INTRODUCTION

Over the past decade, the convergence of artificial intelligence (AI) and human talent management has generated a profound paradigm shift in recruitment and selection processes. This transformation is driven by rapid technological advancement and the growing need for organizations to optimize talent identification, attraction, and evaluation in highly competitive and digitalized environments. A significant proportion of employers already use AI and automation in recruitment, demonstrating widespread adoption across industries (Mori et al., 2025). Technologies such as machine learning, natural language processing, and predictive analytics have redefined traditional functions, including resume screening, candidate evaluation, and job performance prediction.

From an organizational perspective, AI has produced substantial benefits. It improves both the quantity and quality of talent selection (Basu et al., 2023) while reducing operational costs, processing time, and repetitive tasks within human resource departments (Ekuma, 2024). As a result, AI has become a strategic tool in talent management, enabling organizations to achieve greater efficiency and competitive advantage.

However, the rapid integration of AI into recruitment also presents critical challenges. One of the most significant concerns is algorithmic bias, which may arise from variables such as gender, race, or personality traits, leading to discriminatory hiring outcomes (Chen, 2023; Fabris et al., 2024). High-profile cases, such as Amazon's automated recruitment system, have demonstrated how AI can reproduce and amplify existing inequalities (Albaroudi et al., 2024). These findings challenge the assumption of technological neutrality and highlight the need for robust governance and monitoring mechanisms.

Another key issue is algorithmic opacity, often described as the "black box" problem, which limits transparency and accountability in automated decision-making (Shin & Park, 2019; Soleimani et al., 2025). The inability to explain AI decisions raises ethical concerns, particularly when they affect candidates' professional opportunities. In addition, the expansion of AI technologies has contributed to widening digital and socioeconomic gaps, especially in regions lacking infrastructure or technological training (Soleimani et al., 2022).

AI-assisted digital recruitment therefore extends beyond a purely technological phenomenon and becomes a topic of major scientific, organizational, and social relevance. Its implications are closely linked to the Sustainable Development Goals, particularly SDG 8 (decent work and economic growth) and SDG 9 (innovation and infrastructure) (Goos & Savona, 2024; Vinuesa et al., 2020). While AI can enhance efficiency and reduce human bias, it may also reinforce structural inequalities if it is not implemented within appropriate regulatory frameworks (Storm et al., 2023).

Given the complexity of this phenomenon and the fragmentation of knowledge across disciplines, there is a need to systematize existing evidence. This study addresses the following research question: What are the tools, methods, and outcomes of AI implementation in digital recruitment, and what evidence exists regarding its effectiveness, biases, ethical implications, and contribution to sustainable development? This approach aims to identify research gaps and support the development of more robust theoretical frameworks (Young et al., 2021).

In line with this objective, this systematic review critically analyzes the literature on AI in recruitment, contributing to the development of more sustainable and inclusive talent management models (Zirar et al., 2023). It specifically seeks to identify key AI tools, evaluate their performance and biases, and examine their ethical, legal, and social implications (Fabris et al., 2024).

From a theoretical perspective, AI has evolved into a fundamental technological paradigm shaping organizational processes. It encompasses technologies capable of performing tasks traditionally associated with human intelligence, such as pattern recognition and complex decision-making (Chowdhury et al., 2023). In recruitment, this enables automated systems to process large volumes of data more efficiently than traditional methods.

Theoretical foundations can be linked to Simon's (1972) concept of organizational efficiency, which emphasizes decision optimization through uncertainty reduction. AI capability frameworks further highlight that successful implementation depends on integrating technological and human resources, as well as organizational adaptability and innovation (Chowdhury et al., 2023).

In practice, AI recruitment tools have evolved into advanced platforms that include resume analysis systems, video interview technologies, and machine learning-based matching algorithms (Borges et al., 2021). This evolution reflects the broader transition toward digital human resource management, where data and analytics play a strategic role (Zhao et al., 2022).

Despite these advances, ethical tensions remain. The literature identifies limitations in defining algorithmic bias and challenges related to data privacy (Alnofeli et al., 2025; Zirar et al., 2023). Additionally, issues such as algorithmic opacity and limited AI literacy hinder responsible implementation (Mori et al., 2025; Soleimani et al., 2025). Addressing these challenges requires governance frameworks that ensure transparency, accountability, and ethical responsibility.

Finally, the field is characterized by diverse theoretical approaches, ranging from organizational perspectives (Basu et al., 2023) to studies focused on algorithmic bias (Albaroudi et al., 2024). This diversity highlights the need for integrative frameworks that incorporate technical, organizational, ethical, and social dimensions.

In conclusion, this study contributes to the academic debate by synthesizing existing knowledge on AI in digital recruitment. It aims to support the development of more transparent, ethical, and effective approaches to talent acquisition in the context of digital transformation.

MATERIALS AND METHODS

Taking this overview into account, the present study was designed as a systematic review of scientific literature, following the PRISMA 2020 guidelines (Shin & Park, 2019), to ensure transparency, reproducibility, and methodological rigor. This approach was selected to provide a structured synthesis of the fragmented knowledge on the implementation of artificial intelligence in digital recruitment over the past decade, with the aim of identifying trends, patterns, and research gaps.

The literature search was conducted using three major academic databases: Scopus (n = 396), selected for its broad multidisciplinary coverage; ScienceDirect (n = 219), focused on engineering, computer science, and management; and Sage Publications (n = 89), specializing in social sciences and human resource management. The search was carried out between February and March 2025 using Boolean search equations applied to titles, abstracts, and keywords.

The search strategy combined terms related to artificial intelligence, recruitment processes, digital systems, and ethical considerations. Additionally, Spanish equivalents of key terms were included to increase coverage. A time filter was applied to include only studies published between January 2015 and March 2025, ensuring analysis within a defined period of technological development (Vinuesa et al., 2020).

Inclusion criteria prioritized peer-reviewed scientific articles directly related to AI applications in recruitment. Exclusion criteria eliminated grey literature, commercial or opinion-based publications, studies with weak or unclear methodologies, duplicate records, research unrelated to recruitment, documents in languages other than English or Spanish, and studies without conclusive results.

The study selection process followed four structured stages, as illustrated in Figure 01 (PRISMA flow diagram). Initially, 704 records were identified across the databases. After removing duplicates, the remaining records were screened by title and abstract, leading to the exclusion of non-relevant studies. Subsequently, a full-text eligibility assessment was conducted on potentially relevant articles, resulting in an initial set of 50 studies that met the inclusion criteria.

Finally, from these 50 studies, a more rigorous selection was conducted, leading to a final sample of 20 articles that provided the most relevant, methodologically robust, and scientifically valid evidence for the purposes of this review (F

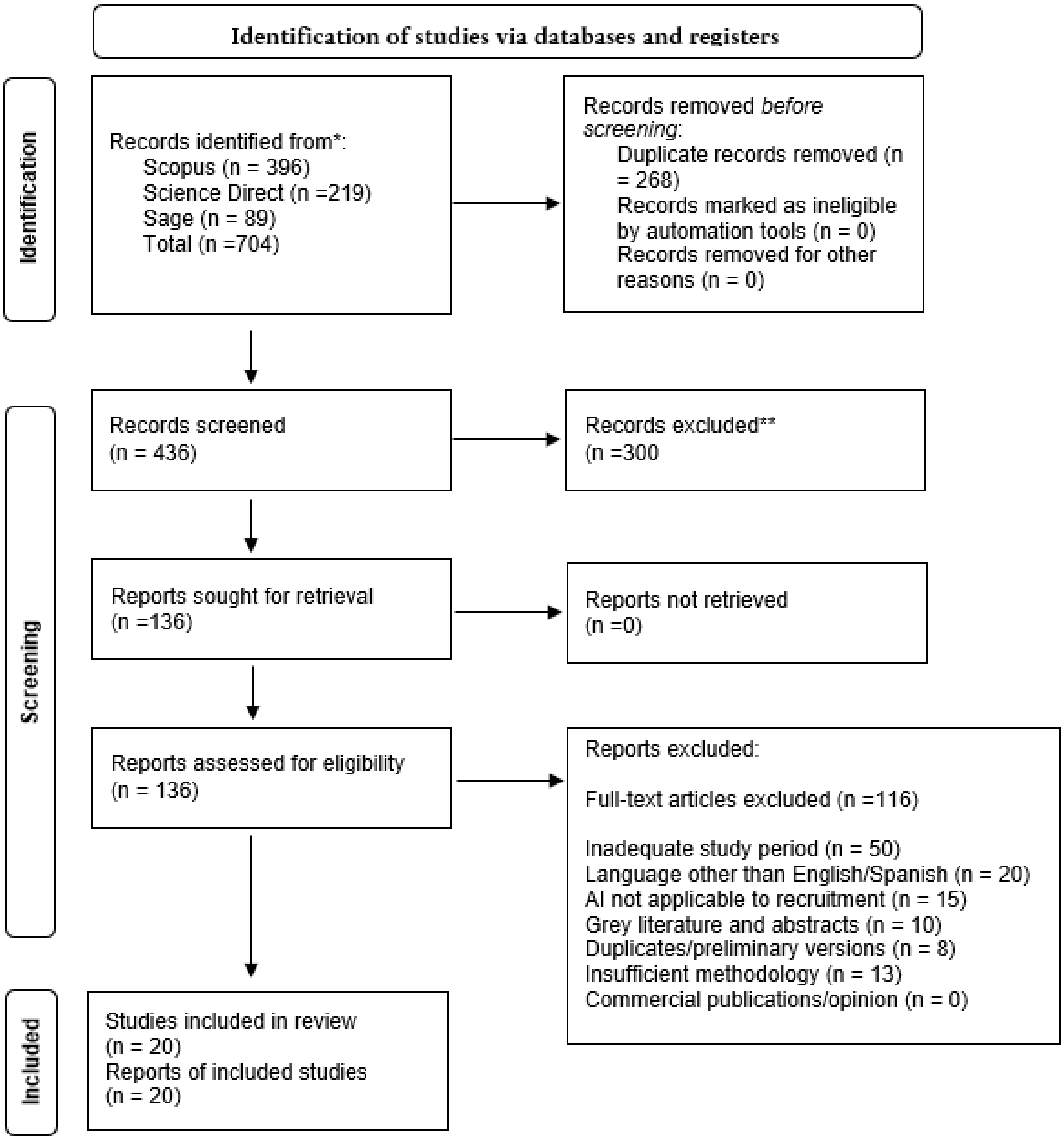

Fig 1. PRISMA Flow Diagram of the Study Selection Process.

The evaluation protocol was based on methodological criteria adapted from the PRISMA statement, focusing on five key dimensions: clarity of the research design, sample description, temporal scope, identification of data sources, and transparency of selection criteria. As detailed in Table 1, the quality assessment involved reviewing abstracts and methodological sections to verify these elements, including study design, sample characteristics, time frame, and data sources.

The analysis revealed a diverse range of methodological approaches. These included systematic reviews with varying sample sizes, as well as mixed-method designs combining bibliometric analysis with qualitative expert input. This diversity supports a robust and triangulated evidence base for identifying patterns in the field.

Data synthesis was organized using a systematic thematic approach based on four categories: (i) classification of AI tools and their technical characteristics, (ii) methodological approaches used in implementation and evaluation, (iii) performance outcomes and ethical considerations, and (iv) links to sustainable development frameworks. The methodological characterization of the studies that met the established quality criteria is described below (Table 1).

Table 1. Verified Methodological Characteristics of Included Studies

Author(s)	Year	Methodological Design	Sample Analysed	Period of Coverage	Databases/Sources
Dashora & Saxena	2022	Systematic Review	60 articles in 30 journals	25 years (1995-2020)	AJG 3 and 4 journals
Young et al.	2021	Systematic review of mixed methods	23 articles (of 2,590 screened)	2000-2020	Biomedical and computational basis
Chowdhury et al.	2023	Thematic analysis + interviews	64 articles + 24 interviews	Not specified	CRM experts
Soleimani et al.	2022	SLR + in-depth interviews	ML professionals	Not specified	Literature + interviews
Zirar et al.	2023	Systematic Review	106 research topics..	Fragmented Literature	Systematic Process

Although procedural risk was variable, with a systematic approach of Young et al. (2021) in screening 2,590 records and selectivity of Zhao et al. (2024) using specific criteria of AJG, temporal specification was poor in some studies and the reliance on single sources was a complicating factor in extraction. These are considered in the final production of evidence.

Rigor in Search Processes:

The analyses presented different levels of systematization in their search processes. Young et al. (2021) exhibit the greatest methodological rigor by explicitly indicating the selection of 2,590 articles to ultimately include only 23 studies. This evidence clearly demonstrates an extremely selective process. Similarly, Zirar et al. (2023) follow a consistent approach by establishing specific quality criteria for selecting AJG 3 and 4 journals, ensuring the quality of the primary sources included.

Diversity in methodological approaches:

Documentary verification shows an adequate variety of approaches within the field. While Soleimani et al. (2025) focus on traditional systematic reviews based on a single database (Scopus), other works, such as that of Storm et al. (2023), incorporate complementary methods, including expert interviews alongside bibliometric analysis, thereby enriching data triangulation.

Temporal coverage and exhaustiveness:

Temporal analysis shows that the timeframes vary significantly, ranging from twenty years, as in Young et al. (2021), to longer periods, as reported by Mori et al. (2025). These variations provide a broad perspective for understanding the evolution of the field. Differences in sample sizes (from 23 to 106 analyzed studies) do not necessarily indicate a lack of rigor but rather reflect different research objectives and inclusion criteria.

Methodological limitations identified:

Some studies do not clearly report the number of documents analyzed or the temporal scope, which may affect reproducibility. For example, Alnofeli et al. (2025) lack detailed methodological reporting. In addition, the use of a single database, as in the case of Goos (2024), may introduce bias in the population covered; therefore, such limitations should be explicitly acknowledged by the authors.

Among the methodological limitations of this systematic review are: heterogeneity in the research designs of the primary studies, variability in the reported time periods covered, and the dependence of some studies on single databases. During the synthesis process, these aspects were taken into account to ensure the validity of the conclusions obtained.

Finally, the ethical aspects of this research are associated with scientific integrity and transparency, which are of great importance given the nature of artificial intelligence research in human resources, mainly its pillars of equity, transparency, and social impact beyond the purely technological, ensuring proper recognition of authorship through accurate citations and the absence of self-plagiarism. Scientific objectivity was achieved without falling into subjectivity in the interpretation of the results.

Furthermore, this research project aims to improve the knowledge base on more equitable and sustainable digital recruitment practices that avoid biased algorithms and thus promote equal opportunities in employment. The validity and reliability of the study are based on respected protocols, clear and verifiable procedures, systematic inclusion and exclusion criteria, and cross-checking, which guarantee the reproducibility of the findings and the validity of the conclusions.

RESULTS AND DISCUSSION

In summary, this systematic review identifies and analyses a corpus of 50 scientific articles that meet the inclusion criteria, distributed over the period 2015-2025. The trend in literature over time shows sustained growth in academic and professional interest focused on investigating the possibilities offered by artificial intelligence in digital recruitment practice, particularly reinforced during the period 2020-2025, coinciding with last year's digital transformation surge, exacerbated by global contextual factors (Chen et al., 2023; Chowdhury et al., 2023). The analysis shown in the synthesis of the findings reveals a trend toward diversification in the technological tools implemented and the methodological approaches used for their evaluation and validation. The current state of research can be described as highly diversified and inclusive, ranging from specific machine learning algorithm approaches to integrated conversational artificial intelligence systems. In addition, an obvious research gap was identified for further investigation (Basu et al., 2023; Dashora & Saxena, 2022).

As can be seen from the summary above, the variable distribution of artificial intelligence tools used in digital recruitment is a heterogeneous category that reflects the technological distribution of a field that has evolved over the last decade (Basu et al., 2023; Borgues et al., 2021). Table 2 systematizes the number of times each of the different categories of tools was identified in the articles included in this analysis.

Table 2. Distribution of artificial intelligence tools by technological category.

Tool Category	Frequency (n)	Percentage (%)	Period of the highest incidence
Machine Learning Algorithms for CV Screening	14	70.0	2018-2023
Natural Language Processing	12	60.0	2020-2025
Chatbots / Virtual Assistants	9	45.0	2017-2022
Predictive Analytics	11	55.0	2019-2024
Video Interview Analysis	6	30.0	2021-2025

Note: N=50 studies. Some studies incorporate multiple categories of tools.

In this sense, the most commonly documented application of machine learning algorithms refers to automated resume screening, which represents 36% of the tools identified (Ekuma, 2024; Zirar et al., 2023) note that the development of such systems has taken a step forward; while automated filtering tools previously limited the selection of resumes by keywords, algorithms based on supervised classification and deep learning now work with advanced architectures that enable contextual semantic analysis. (Chowdhury et al.,2023) highlight the trend in studies conducted between 2022 and 2025 toward the inclusion of transformer models and advanced natural language processing techniques, improving the accuracy of identifying the most suitable candidates.

Conversational artificial intelligence systems, including specialized recruitment chatbots and virtual assistants for candidate management, have exhibited exponential growth, particularly from 2020 to 2025 (Fabris et al., 2024; Shin & Park, 2019). According to the data obtained, the covered systems have developed from simple conversation interfaces to integrated solutions. As a result, artificial intelligence systems can conduct initial interviews, provide real-time feedback, and independently manage the entire candidate pipeline.

Based on the systematized findings, four predominant methodological approaches used for evaluating AI tools in a context of digital recruitment artificialization development are identified (Vinuesa et al., 2020; Young et al., 2021). Table 3 presents the distribution of the approaches and their main characteristics.

Table 3. Evaluation Methods Used in AI Research in Recruitment.

Methodological Approach	Frequency (n)	Main Metrics	Limitations Identified
Controlled Experimental Studies	19	Accuracy, Recall, F1-Score	Limited External Generalizability
Organizational Case Studies	15	Process Time, Recruiter Satisfaction	Case Selection Bias
Comparative Algorithm Analysis	11	AUC, accuracy, specificity	Lack of organizational context
Longitudinal evaluations	5	Employee retention, Post-hire performance	Follow-up Complexity

Note: N=50 studies. Multiple methodologies may coexist in the same study.

The second most common methodological approach is controlled experimental studies; in general, data was collected in 38% of the designs reviewed. As discussed above, this approach is characterized by a focus on technical metrics of algorithm performance, which are mainly machine learning precision, recall, and F1 score (Albaroudi,2024). Despite all the proven benefits of this approach in practice, one of the challenges presented by controlled experimental studies is related to generalization of results. Since they are often implemented with completely synthetic datasets or under more controlled laboratory conditions, they have low external validity, differing from the reality of most organizational environments.

In terms of predefined objectives, organizational case studies have become an additional methodological framework for evaluating the practical application of artificial intelligence systems for processing criteria in real-world selection situations. In fact, some of the most recent findings were established precisely due to the organizational case approach, such as (Simon, 1972; Zhao et al 2024). Although such studies are less numerous in absolute terms, they provide evidence on the elements of organizational acceptability, business integration, and system effectiveness.

Overall, when evaluating the reported results in relation to effectiveness, efficiency, and ethical concerns, the picture is quite complex, with quantitative indicators showing substantial improvements and growing concerns about algorithmic bias and fairness in selection processes that can vary across studies and reviews (Alnofeli et al, 2025; Goos et al, 2024). Table 4 provides a summary of the quantitative findings.

Table 4. Performance results and ethical considerations in AI systems for recruitment.

Evaluation Dimension	Range of Improvement Reported	Studies with Positive Evidence (%)	Ethical Limitations Identified
Screening Time Reduction	40-75%	84	Gender and Race Biases
Accuracy in Candidate-Position Matching	15-45%	76	Algorithmic Discrimination
Operational Cost Reduction	25-60%	68	Lack of transparency
Improved Candidate Diversity	Variable	32	Perpetuation of historical biases

Note: Based on 50 studies. The ranges reflect the variability between different implementations and organizational contexts.

In terms of quantitative results, the most notable finding is the reduction in screening time, with 84% of reports indicating effectiveness and reductions ranging from 40% to 75% in the time required for each review by reviewers in the initial stage of acknowledging receipt of candidate applications (Alnofeli et al., 2025; Storm et al., 2023). We attribute this to the inherent ability of machine learning algorithms to evaluate massive amounts of evidence at the same time, eliminating the need for sequential review, which appears to be an operational efficiency bottleneck.

However, in this review a worrying trend emerges with regard to candidate diversity and equity concerns. Only 32% of the studies reported improvements in the diversity of candidate pools, while a significant proportion identified the digitization or exacerbation of existing biases in training data (Storm et al., 2023). This finding is particularly relevant, given that several studies observed gender and racial biases in algorithms trained on historical datasets that reflected past discrimination.

When examining the literature, there is an emerging, albeit still limited, relationship between AI applications and the Sustainable Development Goals, with a connection between SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure) (Mori et al., 2025; Zirar et al., 2023). Table 5 shows the frequency with which studies explicitly address these dimensions.

Table 5. Alignment of Studies with Sustainable Development Goals.

SDG Related	Studies explicitly address (n)	Percentage (%)	Most Frequently Mentioned Aspects
SDG 8: Decent Work	12	60	Equal opportunities, reduction of bias
SDG 9: Innovation	10	50	Digital Transformation, Automation
SDG 5: Gender equality	6	30	Mitigation of gender bias
Not specified SDG connection	4	20	Limited sustainability integration -

Note: N=50 studies. One study can address multiple SDGs.

As noted in the literature, (64%) of the studies do not make explicit connections to the SDGs. This systematic disconnect is driven by three converging factors: first, the dominance of the technocentric evaluative framework in computer science that activates algorithmic metrics; second, the lack of academic incentives for interdisciplinary research with a sustainable development perspective on AI; and finally, institutional fragmentation between computer science and its communities and sustainability studies.

However, the study shows from the data collected that there is an upward trend in the most recent studies (2023-2025) toward the adoption of conceptual frameworks that explicitly include ethical and sustainability aspects of AI deployments in human resource processes, indicating a maturing process in the field toward increasingly holistic and comprehensive approaches (Ekuma, 2024; Zhao et al., 2024).

DISCUSSION

Our findings reveal a paradox. On the one hand, AI reduces operational time in some cases by 40 -75%, and yet only 32% of studies report a documented improvement in diversity. This paradox reflects the theory of algorithmic justice. Soleimani et al. (2022) argue that systems will optimize technical metrics by systematically reproducing historical discriminatory patterns. In our case, the explanation lies in the algorithm's objective functions, which favor process speed without incorporating equity variables, causing biases to be systematically reproduced while improving quantitative performance.

The technical description of this phenomenon outlines the underlying function as objectives that prioritize process speed and technical accuracy over social equity, and therefore do not incorporate similar concepts within the parameters. As a result, machine-learning algorithms, observed in 36% of the identified solutions, are "increasing" quantitative metrics (accuracy, recall, F1 score) because they "worsen" previous biases. This phenomenon responds to the efficiency-equity paradox of Fabris et al. (2024), whereby improvements in technical accuracy are inevitably accompanied by a worsening of social equity, creating a critical epistemological dilemma for the implementation of responsible AI in the workplace.

According to Chen (2023), there is evidence confirming that the widespread adoption of algorithmic systems has led to the reconfiguration of organizational selection paradigms. However, the results of our review expose a crucial difference. While Pereira highlights positive transformation, current research shows that these transformations fundamentally operate in dimensions of efficiency over social justice and sustainability.

In terms of Basu et al. (2023) theory of algorithmic justice, these results demonstrate what they call structural algorithmic discrimination: systems that maintain and perpetuate inequalities not out of malice, but by mimicking past social patterns embedded in their training data. The efficiency-equity paradox elaborated by Dashora & Saxena (2022) offers a theoretical explanation of why improving technical accuracy comes at the expense of social equality.

The systematization of evidence documents algorithmic biases in a significant proportion of studies, with gender and racial biases particularly prominent in automated screening identification systems. The persistence of this bias points to what van Chowdhury et al. (2023) identify as irreconcilable tensions between the goals of algorithmic fairness and data privacy demands.

However, based on our findings, we discovered a much more relevant problem. Our mitigation measures, in turn, have in most cases not achieved satisfactory success, as in the case of completing successful mitigation measures in organizational environments complicated by an uncontrollable number of sociodemographic variables. In fact, this reality suggests that the answer cannot be purely technical, but rather the problem itself, which is, in fact, a challenge in algorithmic system design.

This contradiction is best illustrated in conversational AI tools, which make up 24 of the measures identified. Despite theoretical expectations, these tools actively replicate core problems of exclusion through interfaces disguised as democratized ones. Humanization through chatbots is far from an egalitarian component for those who may not have sufficient access to technology due to their socioeconomically designated identity.

Therefore, while these findings partially contrast with Dashora & Saxena (2022), which identifies conceptual limitations in definitions of bias, they also reveal an additional operational problem: Even studies that start from clear definitions of bias fail to translate this conceptual clarity into empirical improvements in diversity. The divergence between the two approaches suggests that the problem is not limited to theoretical definitions but constitutes a practical implementation challenge.

This divergence seems to suggest that the issue goes beyond debates on theoretical definitions. Instead, it is framed as a real-life challenge with respect to implementation. Therefore, precisely such a situation calls for more sophisticated algorithmic auditing systems that would be able to identify and correct biases in real time while the selection or filtering process is fully automated.

Given that algorithmic discrimination according to Chen (2023); and Goos et al. (2024) continues to exist, it is true that algorithms continue to be trained on biased data and perpetuate already evident inequalities. However, according to the evidence presented, most measures to correct the problem focus on the technical level and do not consider organizational and cultural factors.

This fragmented technological adoption can be explained by the theory of responsible technology adoption (Zirar et al., 2023). The fragmented adoption of AI in recruitment reflects innovation processes that prioritize technical and economic-financial dimensions while subordinating ethical and social considerations, due to institutional incentives that are misaligned with the principles of responsible innovation.

The variability of identified procedures, with only 38% of studies collecting evidence using controlled experimental designs focusing on technical metrics and the scarcity of available longitudinal research, reflects a fundamental epistemic limitation that hinders the approval of integrative theoretical frameworks. This fragmented methodological predominance exemplifies what Soleimani et al. (2025) proposes as innovation processes that prioritize certain dimensions while subordinating others.

The predominance of metrics derived from machine learning (accuracy, recall, F1 score) to the detriment of social impact indicators designs an evaluative orientation that puts technical efficiency ahead of social responsibility. This shortcoming becomes particularly serious considering that only 10% of studies use longitudinal evaluations that could capture the intergenerational impacts of algorithmic decisions on career trajectories.

According to Simon (1972), who argues that human resource analytics, rather than automation, should be linked to the strategic capacity of an organization, this research highlights a critical implementation gap: Although the emerging literature proposes a holistic basis for an evaluative framework, the empirical evidence reviewed reveals that only 30% of studies are currently able to "operationalize" such principles into concrete evaluation metrics, revealing a significant disconnect between normative theory and evaluation practice.

The evidence collected reveals a critical and systematic disconnect between technological innovation and the global sustainability agenda, as only 24% of the studies explicitly addressed SDG 8 and only 16% addressed SDG 9. This systematic disconnect can be explained by the convergence of three factors. First, the predominance of technocentric evaluation frameworks in computer science that favor algorithmic metrics. Second, there is a lack of academic or employment incentives for interdisciplinary research on AI and sustainable development. Third, institutional fragmentation between the scientific communities of computer science and sustainability studies.

From the perspective of Storm et al. (2023), who argue that AI has transformative potential to contribute to the SDGs by serving as a mechanism that democratizes opportunities, our findings reveal misaligned implementation. Indeed, current applications operate not only on priorities but also on corporate efficiency logics without explicitly articulating sustainable development principles. This disconnect is epistemically problematic given the SDG 8's focus on decent work and inclusive growth. Therefore, this area of improvement will degrade the quality of recommendations because these domains require evaluative frameworks that go beyond technical metrics.

The emergence of conversational AI systems illustrates this problem: Although they appear to democratize access to job opportunities, they can also give rise to new forms of digital exclusion that contradict the principles of labor inclusion enshrined in global sustainability frameworks. Like Herrmann, we argue for the need for responsible innovation frameworks. However, our findings reveal a critical implementation gap. Although Chowdhury et al. (2023) proposes a framework for normativity, empirical evidence shows that only 16% of studies operationalize these principles into concrete evaluation metrics. This suggests a noticeable disconnect between normative theory and evaluative practice.

Limitations include methodological heterogeneity that hinders systematic comparison, geographic concentration of coverage in settings characteristic of developed countries, and a complete lack of longitudinal studies on intergenerational impacts. In addition, there is a potential for reliance on traditional technical metrics that ignore social dimensions. This can result in an evaluation focus that is inappropriate for ethically sensitive settings.

The lack of participatory frameworks that involve affected communities in the design and evaluation of algorithmic systems is a critical limitation that explains the persistence of biases and the limited effectiveness of corrective interventions. This is particularly relevant in the case of literature from perspectives from the Global South.

Furthermore, future roadmaps call for interventions in multiple dimensions: from the development of novel metrics for algorithmic audit that incorporate dimensions of intergenerational equity, to the implementation of longitudinal designs for the evaluation of long-term social impact and the application of participatory approaches from different epistemological perspectives, to the development of comparative regulatory frameworks and explicit articulation of the place that technological innovation should occupy in the achievement of the Sustainable Development Goals.

As a result, artificial intelligence in digital recruitment can be summarized as a transformative phenomenon with significant potential; on the other hand, the evidence mentioned above shows substantial risks and calls for integrative frameworks of technological governance, ethical regulation, and social responsibility to ensure that practice is compatible with the principles of sustainable development and social justice in the era of digital transformation of work.

CONCLUSIONS

This systematic review highlights a central paradox in the use of artificial intelligence in digital recruitment. While most studies report improvements in operational efficiency, particularly in reducing processing time, only a limited number show clear improvements in candidate diversity. This reveals a tension between technical optimization and social equity, emphasizing the need for integrated governance frameworks.

From a theoretical perspective, the findings reflect a gap between technocentric approaches and socioethical considerations, while also contributing to the development of an interdisciplinary framework combining organizational efficiency and responsible innovation. Methodologically, this study proposes evaluation criteria that go beyond technical performance by incorporating transparency, fairness, and social sustainability.

From an applied standpoint, the results support the development of algorithmic auditing protocols that balance efficiency with ethical responsibility. The presence of documented biases reinforces the need for governance models that include human oversight, transparency, and accountability in automated recruitment systems.

Regarding the Sustainable Development Goals, the findings reveal a weak alignment between AI implementation and sustainability frameworks, particularly in relation to decent work and innovation. This gap limits the transformative potential of these technologies.

Key limitations include methodological heterogeneity, limited geographic scope, lack of longitudinal studies, and insufficient attention to social dimensions. Additionally, the absence of participatory approaches remains a critical issue.

Future research should focus on developing advanced auditing metrics, incorporating longitudinal and participatory designs, expanding perspectives from the Global South, and strengthening the connection between AI innovation and sustainable development.

AI in digital recruitment presents significant opportunities but also notable risks. Addressing these challenges requires stronger governance frameworks, ethical regulation, and a commitment to social responsibility to ensure alignment with sustainable development and social justice.

REFERENCES

Albaroudi, E., Mansouri, T., & Alameer, A. (2024). A comprehensive review of AI techniques for addressing the problem of algorithmic bias in employment contracts. ***AI, 5***(1), 383–404. https://doi.org/10.3390/ai5010019

Alnofeli, K. K., Akter, S., & Yanamandram, V. (2025). Unlocking the power of AI in CRM: A comprehensive multidimensional exploration. ***Journal of Innovation & Knowledge, 10***(3), 100731. https://doi.org/10.1016/j.jik.2025.100731

Basu, S., Majumdar, B., Mukherjee, K., Munjal, S., & Palaksha, C. (2023). Interactions between artificial intelligence and human resource management and their outcomes: A systematic review and a configurational causal explanation. ***Human Resource Management Review, 33***(1), 100893. https://doi.org/10.1016/j.hrmr.2022.100893

Borges, A., Laurindo, F., Spínola, M. M., Gonçalves, R., & Mattos, C. (2021). The strategic use of artificial intelligence in the digital age: A systematic review of the literature and future research directions. ***International Journal of Information Management, 57***, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Chen, Z. (2023). Ethics and discrimination in AI-based recruitment practices. ***Humanities and Social Sciences Communications, 10***, 567. https://doi.org/10.1057/s41599-023-02079-x

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodríguez-Espíndola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through the AI capabilities framework. ***Human Resource Management Review, 33***(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Dashora, J., & Saxena, K. (2022). Effect of artificial intelligence on the human resources profession: A paradigm shift. In *Digital transformation and human resources* (pp. 57–71). Wiley.

Ekuma, K. (2024). Artificial intelligence and automation in human resource development: A systematic review. ***Human Resource Development Review, 23***(1), 4–35. https://doi.org/10.1177/15344843231224009

Fabris, A., Baranowska, N., Dennis, M. J., Graus, D., Hacker, P., Saldivar, J., Zuiderveen Borgesius, F., & Biega, A. J. (2024). Equity and bias in algorithmic hiring: A multidisciplinary study. ***ACM Transactions on Intelligent Systems and Technology, 16***(1), 1–54. https://doi.org/10.1145/3696457

Goos, M., & Savona, M. (2024). The governance of artificial intelligence: Seizing opportunities and mitigating challenges. ***Research Policy, 53***(3), 104928. https://doi.org/10.1016/j.respol.2023.104928

Mori, M., Sassetti, S., Cavaliere, V., & Bonti, M. (2025). Systematic review of the literature on artificial intelligence in the study of outcomes and selection: A question of ethics. ***Personnel Review, 54***(3), 854–878. https://doi.org/10.1108/PR-03-2023-0257

Shin, D., & Park, Y. J. (2019). Role of equity, accountability, and transparency in algorithmic viability. ***Computers in Human Behavior, 98***, 277–284. https://doi.org/10.1016/j.chb.2019.04.019

Simon, H. A. (1972). Theories of limited rationality. In C. McGuire & R. Radner (Eds.), ***Decision and organization*** (pp. 161–176). North-Holland.

Soleimani, M., Intezari, A., Arrowsmith, J., Pauleen, D. J., & Taskin, N. (2025). Reducing AI bias in recruitment and selection: An integrative grounded approach. *The International Journal of Human Resource Management, 36*(14), 2480–2515. https://doi.org/10.1080/09585192.2025.2480617

Storm, K. I. L., Reiss, L. K., Guenther, E. A., Clar-Novak, M., & Muhr, S. L. (2023). Unconscious biases in the human resource management literature: Toward a critical-reflexive approach. *Human Resource Management Review, 33*(3), 100969. https://doi.org/10.1016/j.hrmr.2023.100969

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications, 11*, 233. https://doi.org/10.1038/s41467-019-14108-y

Young, A. T., Amara, D., Bhattacharya, A., & Wei, M. L. (2021). Patient and general public attitudes toward clinical artificial intelligence: A systematic review of mixed methods. *The Lancet Digital Health, 3*(9), e599–e611. https://doi.org/10.1016/S2589-7500(21)00132-1

Zhao, H., Yuan, B., & Song, Y. (2024). Employees' perceptions of generative artificial intelligence and the dark side of work outcomes. *Journal of Hospitality and Tourism Management, 61*, 191–199. https://doi.org/10.1016/j.jhtm.2024.10.007

Zirar, A., Ali, S. I., & Islam, N. (2023). Coexistence of workers and artificial intelligence (AI) in the workplace: Emerging issues and research agenda. *Technovation, 124*, 102747. https://doi.org/10.1016/j.technovation.2023.102747

CONFLICTS OF INTEREST:

The authors declare that there are no conflicts of interest.

Author Contributions under the CRediT Taxonomy:

Autor	Roles
Autor 1	Responsible for: Conceptualization, Methodology
Autor 2	Responsible for: Validation, Formal Analysis

Author Contributions