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REVIEW ARTICLES

Algorithmic human resource management and employee well-being: current evidence from a systematic literature review

Gestión algorítmica de los recursos humanos y bienestar laboral: evidencia actual de una revisión sistemática de la literatura

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Abstract

This study examines the relationship between artificial intelligence (AI), algorithmic human resource management, and employee well-being through a systematic review of the scientific literature published between 2020 and 2026. The review addresses the growing need to understand how algorithm-supported decision-making influences employee experience, psychological well-being, organizational trust, and perceptions of fairness in contemporary workplaces. The study followed the PRISMA 2020 guidelines and included peer-reviewed articles retrieved from Scopus, Web of Science, ScienceDirect, and SpringerLink. Following the identification, screening, and eligibility stages, 82 studies were selected for qualitative thematic analysis and descriptive synthesis. The findings indicate that artificial intelligence enhances recruitment and selection, performance evaluation, and human resource analytics while simultaneously introducing challenges related to digital surveillance, algorithmic opacity, technological anxiety, and reduced employee autonomy. Overall, the evidence suggests that algorithmic human resource management can promote employee well-being when implemented within transparent governance frameworks characterized by human oversight, algorithmic fairness, ethical data governance, and active employee participation. The review contributes by synthesizing current evidence, identifying major research trends and knowledge gaps, and highlighting future research priorities, particularly for Latin American organizational contexts, where empirical evidence remains limited.

Keywords artificial intelligence; algorithmic human resource management; employee well-being; human resource analytics; algorithmic fairness.

Resumen

El presente artículo analiza la relación entre la inteligencia artificial, la gestión algorítmica del talento humano y el bienestar laboral, a partir de una revisión sistemática de la literatura científica publicada entre 2020 y 2026. El estudio responde a la necesidad de comprender los efectos que los sistemas automatizados de toma de decisiones generan sobre la experiencia, la salud psicológica y la percepción de justicia de los trabajadores. La metodología siguió las directrices PRISMA 2020 y consideró artículos revisados por pares recuperados de Scopus, Web of Science, ScienceDirect y SpringerLink. Tras el proceso de identificación, cribado y elegibilidad, se incluyeron 82 estudios para el análisis temático y descriptivo. Los resultados evidencian que la inteligencia artificial contribuye a optimizar procesos de reclutamiento, selección, evaluación del desempeño y analítica de recursos humanos; sin embargo, también genera riesgos asociados a la vigilancia digital, la opacidad algorítmica, la ansiedad tecnológica y la pérdida de autonomía laboral. Se concluye que la gestión algorítmica puede favorecer el bienestar laboral cuando se implementa bajo principios de transparencia, supervisión humana, justicia algorítmica y participación de los trabajadores. El estudio propone fortalecer modelos de gobernanza algorítmica centrados en las personas y ampliar la investigación empírica en contextos latinoamericanos.

Palabras clave inteligencia artificial; gestión algorítmica; talento humano; bienestar laboral; justicia algorítmica.

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PUBLIS EDITORIAL

Introduction

The rapid adoption of artificial intelligence (AI) is reshaping human resource management (HRM), which is increasingly supported by predictive analytics, machine learning, and algorithmic decision systems. These technologies enable organizations to process workforce data at scale and support recruitment, performance management, workforce planning, and employee development (Minbaeva, 2021; Strohmeier, 2020).

Human Resource Analytics has contributed to this transformation by allowing organizations to identify workforce patterns, anticipate turnover and performance risks, and support evidence-based interventions. Algorithmic systems now assist HR professionals in screening candidates, evaluating competencies, recommending promotions, and planning staffing needs, thereby increasing the speed and analytical capacity of HR decision-making (Meijerink et al., 2021).

However, technological efficiency does not necessarily imply fair or beneficial outcomes. Algorithmic systems can reproduce historical inequalities when trained on biased data, and their opacity can complicate accountability in employment decisions (Köchling & Wehner, 2020; Raghavan et al., 2020). For this reason, fairness, explainability, and human oversight have become central concerns in algorithm-supported HRM.

Employee trust and acceptance also depend on how these technologies are introduced. Research on algorithmic management shows that monitoring, performance control, and automated decision-making can affect autonomy, perceived justice, and employee well-being, particularly when workers have limited understanding of or influence over the systems that shape their work (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022).

The Job Demands–Resources (JD–R) Model provides a useful framework for interpreting these effects (Bakker & Demerouti, 2017). AI-based technologies may operate as organizational resources when they reduce repetitive work, improve access to information, or support decision-making; conversely, they may become job demands when they intensify surveillance, workload, performance pressure, or insecurity. Empirical evidence from European organizations likewise shows that algorithmic management can influence workplace well-being directly and indirectly through job autonomy and reward practices (Kinowska & Sienkiewicz, 2023).

Recent research therefore suggests that the consequences of AI depend substantially on organizational conditions surrounding implementation. Employee participation, transparent communication, human oversight, and ethical data governance can mitigate risks and strengthen trust, while opaque or highly controlling systems may undermine autonomy and psychological well-being (Budhwar et al., 2022; Parent-Rocheleau & Parker, 2022).

This concern has also acquired regulatory relevance. Regulation (EU) 2024/1689, the Artificial Intelligence Act, establishes harmonized rules for AI systems and reinforces requirements related to risk management, transparency, accountability, and human oversight, including in employment-related contexts (European Parliament & Council of the European Union, 2024).

Despite rapid growth in research on AI and HRM, the evidence remains mixed. Some studies emphasize gains in efficiency, analytics, and employee development, whereas others identify risks associated with surveillance, algorithmic bias, reduced autonomy, technological anxiety, and organizational injustice (Budhwar et al., 2022; Kim et al., 2025; Parent-Rocheleau & Parker, 2022).

These tensions are especially relevant in regions where empirical evidence remains limited. Research on algorithmic HRM and employee well-being is still concentrated in North America, Europe, and parts of Asia, leaving fewer context-specific studies from Latin America and other emerging economies. This geographical imbalance restricts the transferability of existing conclusions and reinforces the need for broader comparative research.

Accordingly, an integrative synthesis is needed to clarify how algorithmic HRM affects employee well-being, identify the organizational conditions associated with positive or negative outcomes, and establish priorities for future research. A systematic literature review offers an appropriate approach for organizing this fragmented body of evidence (Page et al., 2021; Snyder, 2019).

Accordingly, the present study addresses the following research question:

What are the main effects of algorithmic human resource management on employee well-being reported in the recent scientific literature?

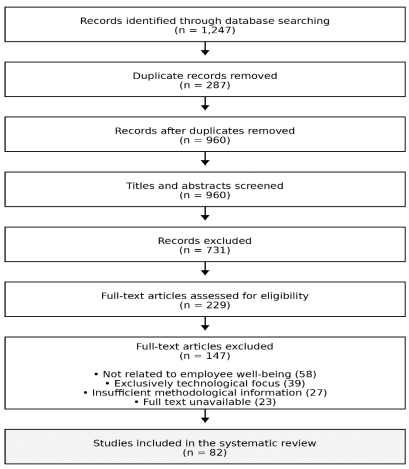
To answer this question, the objective of this study is to systematically analyze scientific evidence published between 2020 and 2026 on the relationship between artificial intelligence, algorithmic human resource management, and employee well-being. The review identifies prevailing research trends, theoretical perspectives, reported benefits and risks, knowledge gaps, and future research priorities for ethical, transparent, and human-centered HRM.

Methodology

This study employed a systematic literature review guided by PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), which supports transparent reporting of identification, screening, eligibility, and inclusion procedures (Page et al., 2021). No prospective protocol registration is reported in the source documentation for this review.

Figure 1 summarizes the study selection process. The search identified 1,247 records; after duplicate removal, screening, and eligibility assessment, 82 peer-reviewed studies published between 2020 and 2026 were retained for qualitative thematic analysis and descriptive synthesis.

Figure 1. PRISMA 2020 Flow Diagram of the Study Selection Pro



Source: Prepared by the authors based on PRISMA 2020 (Page et al., 2021).

The final set of 82 studies constituted the evidence base for examining relationships among artificial intelligence, algorithmic HRM, employee well-being, organizational trust, autonomy, fairness, and related psychosocial outcomes.

A systematic review was appropriate because it enabled structured comparison of evidence across organizational contexts and methodological approaches while supporting the identification of recurrent themes, research gaps, and future research priorities.

The literature search was conducted between January and March 2026 in Scopus, Web of Science Core Collection, ScienceDirect, and SpringerLink.

The search strategy combined terms related to artificial intelligence, algorithmic management, HRM, and employee well-being. A common conceptual search structure was adapted to the syntax available in each database. Exact platform-specific search strings were not preserved in the source records, which is acknowledged as a reproducibility limitation.

The core Boolean structure was: ("Artificial Intelligence" OR "AI" OR "Algorithmic Management" OR "Digital Human Resource Management" OR "HR Analytics") AND ("Human Resource Management" OR "Talent Management" OR "Human Resources") AND ("Employee Well-being" OR "Workplace Well-being" OR "Employee Experience" OR "Occupational Health").

Supplementary combinations of these terms were applied across titles, abstracts, and keywords to improve sensitivity while retaining the predefined eligibility criteria.

Inclusion Criteria

Table 1. Inclusion criteria applied in the systematic literature review

Inclusion Criterion	Description
Document type	Peer-reviewed journal articles.
Publication period	Studies published between 2020 and 2026.
Language	Articles published in English or Spanish.
Research focus	Studies addressing artificial intelligence, algorithmic management, digital human resource management, or HR analytics in the context of human resource management.
Outcome variables	Studies explicitly examining employee well-being, workplace well-being, employee experience, job satisfaction, occupational health, or related psychosocial outcomes.
Availability	Full-text articles available for review and analysis.

Table 2. Exclusion criteria applied in the systematic literature review

Exclusion Criterion	Description
Document type	Books, book chapters, dissertations, conference abstracts, editorials, commentaries, letters, and review notes.
Research focus	Studies exclusively focused on technological or engineering aspects without implications for human resource management or employee well-being.
Duplicates	Duplicate records identified across the selected databases.
Methodological relevance	Studies lacking empirical findings or relevant conceptual contributions related to the research objective.
Accessibility	Publications without full-text access.

Study Selection Process

The study selection process followed four PRISMA stages: identification, duplicate removal, screening, and eligibility. Screening decisions were made against the predefined inclusion and exclusion criteria. The source records do not document formal inter-rater agreement statistic or independent duplicate screening, and no such reliability claim is made here.

Stage 1. Identification

The initial database search yielded 1,247 records, including 518 from Scopus, 326 from Web of Science, 241 from ScienceDirect, and 162 from SpringerLink.

Stage 2. Duplicate Removal

After bibliographic screening using reference management software, 287 duplicate records were removed, resulting in a preliminary dataset of 960 publications.

Stage 3. Screening

Titles and abstracts of the 960 records were screened against the predefined inclusion criteria. During this stage, 731 records were excluded because they did not meet the eligibility requirements.

Stage 4. Eligibility

A total of 229 full-text articles were assessed for eligibility. Of these, 147 were excluded because they did not directly address employee well-being, focused exclusively on technological or engineering issues, provided insufficient methodological information, or lacked full-text accessibility. The final review therefore comprised 82 peer-reviewed studies.

Data Extraction

A standardized data-extraction matrix recorded author(s), year, country, journal, research objective, methodological design, type of AI or algorithmic management examined, HRM process, employee well-being variables, principal findings, and reported limitations. The complete matrix containing bibliographic identification of the 82 included studies forms part of the review dataset referenced in the Data availability statement.

The extracted information was organized in electronic spreadsheets to support comparison, coding, categorization, and synthesis across studies.

Methodological Quality Assessment

Methodological quality was appraised descriptively using seven criteria: clarity of objectives, appropriateness of research design, adequacy of sample description, transparency of data collection, suitability of analysis, consistency of results, and coherence between findings and conclusions. The matrix was used to inform interpretive confidence rather than to generate a weighted quality score or validated cut-off.

Table 3. Methodological quality assessment

Quality criterion	Assessment focus
Clarity of objectives	Clearly defined research objectives
Research design	Appropriate methodological design
Sample description	Adequate description of participants or units of analysis
Data collection	Transparent procedures
Data analysis	Appropriate analytical techniques
Results consistency	Findings supported by the analyses
Conclusions	Conclusions consistent with reported evidence

Source: Prepared by the authors based on the systematic literature review

Studies with clearly insufficient methodological information were excluded during eligibility. For the studies included, the seven-item quality matrix was used as a structured descriptive appraisal; no formal numerical threshold or inter-rater reliability coefficient is reported.

Data Analysis

Extracted data were analyzed through qualitative thematic analysis complemented by descriptive synthesis. Recurring concepts and relationships were coded and grouped into broader analytical dimensions, while descriptive summaries were used for study design, publication year, and thematic distribution.

Table 4. Representative eligible studies from the 2020–2026 review corpus

Author(s)	Year	Country/Context	Research Design	Main Topic	Key Finding
Kellogg et al.	2020	International	Integrative review	Algorithmic control at work	Algorithmic control reshapes direction, evaluation, and discipline, with implications for worker autonomy and control.
Raghavan et al.	2020	United States	Empirical / technical-legal analysis	Algorithmic hiring bias	Automated hiring systems can reproduce or obscure discriminatory patterns when data and validation practices are inadequate.
Meijerink et al.	2021	International	Conceptual review	HRM and algorithms	Algorithmic systems redistribute HRM activities and raise questions about human agency, responsibility, and governance.
Budhwar et al.	2022	International	Review	AI and international HRM	AI creates HRM opportunities and risks whose effects depend strongly on organizational and institutional context.
Parent-Rocheleau & Parker	2022	International	Review	Algorithmic management and work design	Algorithmic management can alter job resources and demands, including autonomy, workload, and monitoring, with consequences for well-being.
Kinowska & Sienkiewicz	2023	European organizations	Quantitative	Algorithmic management and well-being	Algorithmic management is associated with workplace well-being directly and indirectly through job autonomy and reward practices.
Kim et al.	2025	International	Review	Strategic HRM and algorithmic technologies	Algorithmic technologies reshape work design and HR delivery; human agency and organizational context remain central to outcomes.

Initially, the thematic analysis identified a series of emerging categories across the selected studies, including AI-assisted recruitment and selection, algorithmic performance evaluation, human resource analytics, employee well-being, mental health, algorithmic fairness, organizational transparency, employee autonomy, and artificial intelligence ethics.

Subsequently, these categories were synthesized into broader analytical dimensions to identify recurring patterns, dominant research trends, and emerging challenges reported in the recent scientific literature. This analytical process enabled the development of a comprehensive understanding of how algorithmic human resource management influences employee well-being while providing an evidence-based foundation for academic discussion and practical recommendations aimed at fostering responsible AI implementation in organizational settings.

Results and discussion

Table 5. General characteristics of the included studies

Characteristic	Frequency	Percentage (%)
Quantitative studies	37	45.1
Qualitative studies	18	22.0
Mixed-method studies	9	11.0
Systematic reviews	12	14.6
Conceptual studies	6	7.3
Total	82	100.0

Table 5 shows that quantitative studies were the most common design (45.1%), followed by qualitative studies (22.0%), systematic reviews (14.6%), mixed-method studies (11.0%), and conceptual studies (7.3%). This distribution indicates a growing but methodologically diverse evidence base on algorithmic HRM and employee well-being.

Table 6. Distribution of studies by publication year

Publication Year	Number of Studies	Percentage (%)
2020	8	9.8
2021	10	12.2
2022	14	17.1
2023	17	20.7
2024	18	22.0
2025	11	13.4
2026	4	4.8
Total	82	100.0

Publication output increased from 2020 to 2024, when the annual count reached its highest level in the review corpus. The lower counts in 2025 and 2026 should be interpreted in light of the search cutoff rather than as evidence of declining research activity.

Table 7. Main thematic categories identified in the systematic review

Thematic Category	Number of Studies	Percentage (%)
AI-assisted recruitment and selection	21	25.6
Algorithmic performance evaluation	16	19.5
Employee well-being and mental health	15	18.3
Algorithmic fairness and transparency	13	15.9
Human resource analytics	9	11.0
Digital ethics and algorithmic governance	8	9.7
Total	82	100.0

Recruitment and selection represented the largest thematic category, while digital ethics and algorithmic governance were less frequently represented. This imbalance suggests that operational HR applications have received greater attention than the governance conditions required for responsible implementation.

Across the 82 studies, five recurring domains were identified: AI-assisted recruitment and selection, algorithmic performance evaluation, employee well-being and mental health, algorithmic fairness and organizational trust, and ethical challenges in HRM. Together, these domains capture both the organizational opportunities and psychosocial risks associated with algorithmic HRM.

The reviewed evidence was concentrated mainly in technologically advanced economies, while Latin American studies were comparatively scarce. This geographical concentration limits context-specific understanding of algorithmic HRM in emerging economies and supports the need for broader cross-regional research (Budhwar et al., 2022).

AI-Assisted Recruitment and Selection

AI-assisted recruitment and selection is one of the most extensively studied applications. Organizations use algorithmic tools to screen résumés, classify competencies, and support employment decisions, but the benefits of speed and scale are accompanied by concerns about data quality, discrimination, and accountability (Meijerink et al., 2021; Raghavan et al., 2020).

The literature reports gains in processing capacity and consistency, yet these advantages depend on the quality of data, model validation, and the extent of human oversight. Algorithmic hiring therefore requires governance mechanisms that combine technical performance with procedural fairness.

A central risk is the reproduction of historical bias. Raghavan et al. (2020) and Köchling and Wehner (2020) show that algorithmic employment systems may create or perpetuate discriminatory outcomes when training data, target variables, or validation procedures reflect pre-existing inequalities.

Overall, technological efficiency does not automatically produce fairer decisions. Without explainability, auditing, and human review, complex models can make discriminatory or unjust outcomes more difficult to detect and contest (Köchling & Wehner, 2020; Raghavan et al., 2020).

Algorithmic Performance Evaluation and Employee Experience

A second research stream concerns algorithmic performance management. Algorithms can monitor output, set goals, schedule work, generate ratings, and support performance-related decisions, thereby reshaping organizational control and employee experience (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022).

These systems can provide timely information and consistency, but benefits depend on how employees experience the resulting work design. Excessive monitoring or automated control may reduce autonomy and increase perceived pressure.

Research on algorithmic management therefore identifies adverse consequences when workers experience continuous surveillance, restricted discretion, or opaque evaluation criteria (Kellogg et al., 2020; Kinowska & Sienkiewicz, 2023).

From the JD–R perspective, algorithmic technologies can simultaneously function as resources and demands. Their effects on well-being depend on whether they improve access to useful information and reduce burdens or instead intensify workload, monitoring, and loss of control (Bakker & Demerouti, 2017; Parent-Rocheleau & Parker, 2022).

Employee acceptance consequently appears closely linked to transparency, participation, perceived fairness, and opportunities for meaningful human influence over algorithm-supported decisions.

Employee Well-Being and Mental Health in Digital Work Environments

The review also identified a consistent relationship between algorithmic work systems and employee well-being. Digital technologies can support well-being when they reduce repetitive tasks, improve access to information, and enable more effective development or workload decisions; they can undermine it when they heighten insecurity, surveillance, or loss of autonomy (Kinowska & Sienkiewicz, 2023; Parent-Rocheleau & Parker, 2022).

Recent HRM scholarship similarly emphasizes that algorithmic technologies reshape work design and HR delivery, making human agency and organizational context central to whether outcomes are beneficial or harmful (Kim et al., 2025).

Negative outcomes include technostress, insecurity, emotional strain, and reduced job satisfaction when workers perceive automation as threatening or highly controlling. These risks reinforce the importance of participatory implementation and safeguards for autonomy and dignity.

Taken together, the evidence suggests that employee well-being is not determined by AI alone but by the interaction between technological design, work organization, leadership, governance, and employee voice (Budhwar et al., 2022; Kinowska & Sienkiewicz, 2023).

Algorithmic Fairness, Transparency, and Organizational Trust

Transparency and fairness emerged as recurrent governance themes. Employees are more likely to accept algorithm-supported HR decisions when criteria are understandable, contestable, and accompanied by meaningful human oversight (Meijerink et al., 2021; Parent-Rocheleau & Parker, 2022).

Opaque "black box" decision processes can increase perceptions of organizational injustice because employees may be unable to understand or challenge how employment-related recommendations are produced. Research on algorithmic bias similarly stresses the need for validation, auditing, and accountability (Kordzadeh & Ghasemaghaei, 2022; Raghavan et al., 2020).

Organizational trust is therefore closely connected to the governance of algorithmic systems. Clear communication, human review, and opportunities to question decisions can help employees perceive AI as a support mechanism rather than an uncontestable form of control.

This interpretation is consistent with Kim et al. (2025), who emphasize that the strategic value of algorithmic technologies depends on how organizations integrate them with human agency and broader organizational systems.

Implications for Strategic Human Resource Management

The findings show that AI is moving HRM toward more data-driven and algorithm-supported models. This creates opportunities for faster analysis and more consistent processes, but it also increases the strategic importance of leadership, ethics, governance, and employee participation.

Organizations that emphasize productivity (Aspiazu-Sánchez & Esquivel-García, 2025) without adequate transparency or human oversight face greater risks of employee resistance, reduced autonomy, and deteriorating well-being. Responsible implementation requires explainability, fairness, data governance, and channels for employee voice.

In this context, competency-based human resource management remains particularly relevant, since the identification and development of occupational competencies provide a foundation for training, performance, and adaptation to changing organizational requirements (Muñoz Sánchez et al., 2021).

Accordingly, the central managerial challenge is not simply adopting advanced technologies but designing governance arrangements that preserve employee rights, dignity, autonomy, and trust while realizing organizational benefits.

Conclusions

This systematic review synthesized recent evidence on artificial intelligence, algorithmic HRM, and employee well-being. The findings show that algorithmic technologies are reshaping recruitment, performance management, analytics, and work design while generating both organizational opportunities and psychosocial risks.

Employee well-being emerges as a multidimensional outcome shaped not only by technological capability but also by transparency, human oversight, fairness, work design, and employee participation. AI can function as a resource when it reduces burdens and supports decisions, but as a demand when it increases surveillance, insecurity, or loss of autonomy.

The review contributes by integrating HRM, organizational psychology, work-design, and digital-governance perspectives. It also highlights the limited geographical diversity of current evidence and the need for more research in emerging economies, including Latin America.

For managers, responsible algorithmic governance should guide implementation. HR professionals should establish clear accountability, explainability, human review, ethical data practices, and digital-literacy initiatives that support informed employee participation.

For policymakers, the growing use of AI in recruitment, promotion, performance evaluation, and career development reinforces the need for safeguards against discrimination and for mechanisms that protect fairness, transparency, and fundamental labor rights.

This review has limitations. It was restricted to peer-reviewed studies retrieved from four major databases and to English- or Spanish-language publications. Exact platform-specific search syntax, formal inter-rater reliability, and prospective protocol registration were not documented in the source records. In addition, rapid technological change may quickly alter the evidence base.

Future research should prioritize longitudinal, cross-cultural, and sector-specific studies on well-being, mental health, trust, autonomy, and job satisfaction, as well as stronger empirical evaluation of algorithmic fairness and governance in emerging economies.

In conclusion, the long-term value of algorithmic HRM will depend on organizations' ability to combine technological innovation with human-centered work design, ethical governance, and sustainable employee well-being.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

Author contribution

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Data availability statement

The datasets used and/or analyzed during the current study, including the data-extraction matrix identifying the 82 included studies, are available from the corresponding author on reasonable request.

Statement on the use of AI

The authors acknowledge the use of generative AI and AI-assisted technologies to improve the readability and clarity of the article.

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