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Influence of Organizational Culture on Employee Engagement: Exploring the Mediating Role of Artificial Intelligence

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Abstract

Workplaces everywhere are changing fast, and nowhere is that change more visible than in how organizations try to keep their people engaged. This paper explores a question that sits at the heart of modern HR management: does organizational culture influence how engaged employees feel at work — and does artificial intelligence play a role in connecting the two? Drawing on a systematic review of 51 peer-reviewed studies published between 2017 and 2026, filtered through the PRISMA framework and analyzed using Biblioshiny-based bibliometric mapping, this study synthesizes a rapidly expanding body of literature that spans management, organizational behaviour, and information systems. Three theoretical frameworks anchor the analysis: Kahn's (1990) psychological conditions model, the Resource-Based View of the firm (Barney, 1991), and Social Exchange Theory (Blau, 1964). Four hypotheses are evaluated through evidence synthesis. The results are clear: organizational culture is a powerful antecedent of employee engagement; AI adoption in HRM tends to strengthen engagement, but only when cultural conditions support it; AI mediates the culture-to-engagement pathway through what this paper calls three channels — enhanced meaningfulness, enhanced psychological safety, and enhanced resource availability; and cultural readiness for digital transformation amplifies the whole effect. The bibliometric data tell a compelling story of their own: publication activity in this domain grew at an annual rate of 29.86%, peaked in 2025, and has reached 99% saturation by 2026 — a Gaussian growth model fits with R^2=0.961. India has emerged as the leading contributor nation, displacing the Western dominance that characterized earlier literature. The paper concludes with practical recommendations for HR leaders and clear directions for the next generation of empirical research.

Keywords: Organizational Culture, Employee Engagement, Artificial Intelligence, Bibliometric Analysis, PRISMA, Knowledge Management, HRM, Digital Transformation

INTRODUCTION

Something has shifted in how organizations relate to their people. The tools have changed, the data flows differently, and decisions that were once made on gut feel are now supported — sometimes replaced — by algorithms. Nowhere is this more apparent than in the management of employee engagement: the degree to which people bring their full selves to work, feel connected to what they do, and stay committed to the organizations they work for.

Organizational culture has always been the invisible architecture beneath engagement. The values an organization holds, the safety it offers people to speak up and take risks, the way leaders treat those below them — these things quietly determine whether employees are merely present or genuinely engaged. Scholars from Kahn (1990) to Saks (2006) have demonstrated this link with rigor, and practitioners have long known it from experience.

What has changed is the arrival of AI. HR analytics platforms, conversational AI assistants, predictive wellness tools, sentiment analysis engines — these technologies are now embedded in the day-to-day experience of employees in ways that would have seemed speculative just a decade ago. They create real opportunities: personalized learning paths, real-time feedback, proactive well-being nudges. But they also introduce real risks: algorithmic opacity, the erosion of human connection, and the surveillance-like feeling that comes when every click and keystroke is being monitored.

The academic literature has mostly examined these dynamics in pairs: culture and engagement in one strand, AI and HR in another. What has been missing is a serious examination of all three together — specifically, whether AI acts as a mediating bridge through which organizational culture transmits its effects on employee engagement. This paper addresses that gap.

Using a PRISMA-guided systematic review of 51 peer-reviewed studies (2017–2026) combined with Biblioshiny-based bibliometric analysis of a 260-paper dataset, this paper offers three contributions: a synthesis of the triadic culture-AI-engagement relationship grounded in evidence; a theoretical model positioning AI as a conditional mediator; and a bibliometric portrait of this research domain at the moment of its saturation — which itself carries implications for where the field needs to go next.

REVIEW OF LITERATURE

The idea that culture shapes engagement is not new, but the evidence for it has become steadily more sophisticated. Kahn's (1990) foundational work gave the field its psychological scaffolding: employees engage when they find their work meaningful, feel psychologically safe, and have the personal resources to bring themselves fully to their roles. Each of these conditions is substantially determined by culture. A culture that celebrates purpose creates meaningfulness; one built on trust creates safety; one that invests in people creates availability.

Saks (2006) extended this by identifying specific organizational antecedents — job resources, perceived support, procedural justice — as the mechanisms through which culture translates into engagement. Bakker and Demerouti (2008) reinforced this with their Job Demands-Resources model, demonstrating that culturally determined resources are the primary buffers against disengagement.

More recent work has focused on the intersection of culture and AI specifically. Bley, Fredriksen, Skjærvik, and Pappas (2022) found that cultures marked by openness, adaptability, and collaborative norms are significantly better at leveraging AI for strategic outcomes — including employee engagement. Shokrollahi (2025) established that cultural alignment with AI-driven processes is a stronger performance predictor than technological investment alone. Murire (2024) documented a bidirectional dynamic: AI adoption reshapes culture, and cultural receptivity shapes how effectively AI is adopted. Rožman, Tominc, and Milfelner (2023) found both linear and non-linear relationships between AI-oriented organizational culture, leadership quality, training investment, and engagement outcomes.

The integration of AI into HR is now well past the experimental phase. Upadhyay and Khandelwal (2018) documented the early wave of AI in recruitment; Marler and Boudreau (2017) built the analytical foundations for HR analytics as a discipline. Tambe, Cappelli, and Yakubovich (2019) mapped the landscape of AI in HRM comprehensively, surfacing recurring concerns around data privacy, algorithmic bias, and cultural resistance — concerns that remain live today.

Minbaeva (2021) made the uncomfortable argument that AI does not simply automate existing HR processes; it demands a fundamental rethinking of organizational culture to support data-driven decision-making. Raisch and Krakowski (2021) named the central tension: the automation-augmentation paradox. Organizations that use AI to replace human judgment tend to underperform those that use it to extend human judgment — and the difference, they argue, comes down to culture.

The bibliometric analysis conducted for this study — drawing on 260 documents tagged with author-provided keywords — offers a useful empirical snapshot of where the field's intellectual energy is concentrated. "Knowledge management" leads with 137 occurrences, followed by "business" (115), "computer science" (103), and "human resource management" (74). This keyword landscape suggests that the research community frames the AI-HRM relationship primarily as a knowledge challenge: how organizations capture, distribute, and act on what they know about their people.

The literature connecting AI to employee engagement has grown quickly, though not always coherently. Hughes, Robert, Frady, and Arroyos (2019) established the foundational view: AI affects engagement in multidimensional ways, with outcomes determined heavily by how tools are implemented and whether employees perceive them as fair. Sari et al. (2020) showed empirically that AI improves engagement when it

personalizes the employee experience. Mittal, Jora, Sodhi, and Saxena (2023) synthesized findings across contexts to conclude that AI tools work best when they are transparent, personalized, and supported by human touchpoints.

More targeted studies have sharpened the picture. Dutta and Mishra (2024) showed that AI-based virtual assistants reduce anxiety and enhance employees' sense of organizational support — two direct antecedents of engagement. Marimón, Mas-Machuca, and Akhmedjanova (2024) demonstrated that trust in generative AI functions as a catalyst for engagement, and that this trust is itself shaped by how transparent and fair the organizational culture is. Navarro, Pulido-Martos, and colleagues (2024) conducted a systematic review of the field from an AI lens and concluded that AI-mediated engagement interventions yield the strongest results when employees are involved in co-designing them.

At the strategic level, Alzeiby, Islam, and colleagues (2025) found that organizations embedding AI into their strategic HRM frameworks consistently report higher engagement scores over time, with culture serving as the key moderating factor. Aulia and Lin (2024) documented the specific case of remote workforces in the Asia-Pacific, where AI-enabled wellness platforms produced significant engagement gains when placed within a genuine culture of organizational care.

Research Hypotheses

Building on this literature, four hypotheses guide the evidence synthesis:

H1: Organizational culture — specifically innovation orientation, psychological safety, and collaborative norms — is positively associated with employee engagement outcomes.

H2: AI adoption in HRM is positively associated with employee engagement, mediated by improvements in personalization, responsiveness, and support experiences.

H3: AI mediates the relationship between organizational culture and employee engagement, amplifying culture's positive effects through AI-enabled HR mechanisms.

H4: Cultural readiness for digital transformation moderates the strength of AI's mediating effect, such that organizations with higher cultural readiness derive greater engagement benefits from AI.

THEORETICAL FRAMEWORK

Three theoretical lenses are woven together to make sense of the culture-AI-engagement relationship. Each illuminates a different dimension of how AI mediates between cultural conditions and engagement outcomes.

Kahn's (1990) Psychological Conditions Framework

Kahn identified meaningfulness, safety, and availability as the three psychological states that determine the depth of employee engagement. Organizational culture shapes all three directly. What AI adds to this picture is a new set of levers: AI tools can deepen meaningfulness by enabling more personalized and purposeful work experiences; they can strengthen felt safety by ensuring fair, transparent, and responsive HR interactions; and they can free up availability by reducing administrative burden and optimizing workload. This makes AI a structural amplifier of whatever cultural conditions already exist — which is why culture must come first.

Resource-Based View (Barney, 1991)

The Resource-Based View holds that organizational capabilities that are valuable, rare, difficult to imitate, and non-substitutable generate lasting competitive advantage. Organizational culture and AI capability both qualify. But their real strategic value, this study argues, lies in their alignment. An innovation-oriented culture that deploys AI thoughtfully creates a capability bundle that competitors cannot easily replicate — and the engagement outcomes that flow from this alignment are themselves a source of advantage through lower turnover, higher discretionary effort, and stronger innovation.

Social Exchange Theory (Blau, 1964)

Social Exchange Theory frames the employment relationship as a sequence of reciprocal investments and returns, governed by norms of fairness and trust. Employees respond to what they perceive the organization is giving them. When AI-enabled HR tools deliver timely support, personalized development, and transparent feedback, employees experience this as organizational investment — and they reciprocate with deeper engagement. The implication is that AI adoption without genuine cultural investment will be read by employees as surveillance rather than support, triggering withdrawal rather than engagement.

Figure 1 summarizes the integrated theoretical model:

METHODOLOGY

Research Design

This study adopts a secondary data analysis design combining a PRISMA-guided systematic literature review with Biblioshiny-based bibliometric mapping. The choice of secondary data is deliberate: the research question asks about the state of a whole scholarly conversation, not about a single organizational context. A systematic review is the appropriate method for synthesizing evidence across multiple studies in a way that is transparent, reproducible, and minimally biased. The bibliometric layer adds quantitative depth — it allows the intellectual architecture of this field to be mapped, measured, and interpreted rather than simply described.

The research design unfolds in four integrated layers: (1) PRISMA-guided literature identification, screening, and selection; (2) descriptive bibliometric analysis covering publication trends, geographic distribution, and journal rankings; (3) Biblioshiny-based scientometric mapping including keyword co-occurrence networks, thematic maps, Multiple Correspondence Analysis (MCA), and clustering dendrograms; and (4) qualitative thematic synthesis distilling patterns and interpretations from the 51 included studies into the paper's core findings.

Search Strategy and PRISMA Selection

Literature was searched across two platforms: Google Scholar (yielding 198 records) and Litmaps (yielding 114 records), using combinations of keywords including "organizational culture", "employee engagement", "artificial intelligence", "HR analytics", "HRM", "digital transformation", and "knowledge management". This returned an initial pool of 312 records. After removing 52 duplicates, 260 unique studies were screened on title and abstract relevance, resulting in the exclusion of 110 irrelevant records. Full-text review of the remaining 150 studies led to the exclusion of a further 85 on grounds of non-HR focus, non-AI context, or methodological quality concerns. A final detailed assessment excluded 14 more, yielding a core analytical sample of 51 peer-reviewed studies spanning 2017 to 2026.

Bibliometric Analysis Approach

The bibliometric layer of the study used the Bibliometrix/Biblioshiny R package with PubMed database integration. After retrieving and merging records, a dataset of 260 documents was assembled. The analyses performed include: annual scientific production trends, average citations per year, country production mapping, most relevant sources by document count, Bradford's Law of Scattering, keyword co-occurrence networks, thematic mapping (centrality vs. density), Multiple Correspondence Analysis for conceptual structure, hierarchical clustering dendrograms, publication lifecycle modeling using a Gaussian growth curve, and cumulative S-curve analysis. Each of these is reported in the Findings section with accompanying figures and interpretation.

FINDINGS

Overview

The bibliometric dashboard for this domain is striking (see Figure 2). Between 2017 and 2026, 260 documents were published across 178 unique sources by 1,722 authors. The annual growth rate of 29.86% places this domain among the fastest-expanding areas of management scholarship. The average document age of 1.67 years reflects how recent most of this literature is. Average citations per document stand at 2.619 — low in absolute terms, but expected given how new most papers are. Co-authors per document average 7.16, and international co-authorship stands at 10.38%, reflecting the collaborative and cross-disciplinary character of research at the AI-HRM intersection.

Publication Trends

The annual production data (Figure 3) tell a vivid story of a field that barely existed before 2020 and then exploded. Publications numbered just 2 in 2017, dipped to zero in 2018, crept up to 7 by 2020, and then took off: 21 in 2023, a striking peak of 143 in 2025, before falling to 21 in 2026 — a figure that reflects incomplete indexing rather than any real decline. The 2026 drop mirrors a pattern seen in other fast-growing research domains when the scholarly conversation reaches saturation before citation databases fully catch up.

The Gaussian lifecycle model applied to this data achieves a remarkable fit of R^2=0.961 (Figure 4). The model places the peak at year 2024.8, estimates peak annual output at approximately 155 papers per year, and calculates a growth duration (Δ) of just 1.9 years — meaning the field rose and fell from emergence to saturation in under two years. The cumulative S-curve confirms that 50% of total projected publications (K=263) were reached by 2024.8, and 99% by 2026.8. The domain has, by these measures, largely exhausted its current framing and is ready for the next conceptual leap.

Geographic Distribution

One of the more surprising findings of this bibliometric analysis concerns geography. The stereotype of management research as Western-dominated holds for this domain only in its early years. By 2026, India has accumulated approximately 150 cumulative publications, pulling well ahead of the United States (~50), Indonesia (~35), and the United Kingdom (~20). This is not merely a volume story. India's growing output reflects a real convergence of factors: a massive IT services industry that is actively deploying AI-enabled HR practices; a rapidly expanding university sector engaged in applied management research; and a growing community of scholars studying AI-HRM intersections in contexts where the stakes — in terms of workforce scale and cultural diversity — are particularly high.

Intellectual Structure

The keyword co-occurrence network (Figure 5) reveals three distinct clusters that together define the intellectual architecture of this domain. The blue cluster groups technology-society-business concepts: "computer science", "business", "political science", "engineering", "economics". These represent the macro-level framing of AI as a societal and economic force. The red cluster — the one most directly relevant to this paper — clusters "knowledge management", "human resource management", "employee engagement", "organizational culture", "transformative learning", "digital transformation", and "competitive advantage". This is the core where the culture-AI-engagement conversation lives. The green cluster captures an occupational health and demographic stream: "humans", "female", "male", "adult", "aged" — reflecting research on how AI-HR interventions affect different employee populations.

The thematic map (Figure 6) adds a second dimension: development. It plots research themes according to their centrality (how connected they are to the field's core) and density (how internally developed they are). Knowledge management, HRM, and human resources appear as Basic Themes — high centrality, still developing density — which means they are central to the discourse but have not yet generated the tight internal literature that "niche" themes have. DEI concepts (diversity, inclusion, equity) sit in a particularly important position: high centrality but low density, meaning they are recognized as important but remain underdeveloped in the empirical literature. This is a genuine gap with practical stakes.

Source Landscape

The most relevant sources by document count include The Lancet (London, England) with 9 documents — a striking finding that reflects the occupational health and AI-wellness research stream intersecting with this domain. The International Journal for Multidisciplinary Research (8 documents), Zenodo (7), the SSRN Electronic Journal (6), and the International Journal of Scientific Research in Engineering and Management (6) round out the top five. The presence of SSRN and Zenodo among the leaders signals that researchers are using preprint channels aggressively, consistent with a fast-moving domain where waiting for formal peer review means being scooped.

Hypotheses Evaluation

Table 2 summarizes the results of hypothesis testing through evidence synthesis across the 51 included studies.

DISCUSSION

The Triadic Model

The central theoretical contribution of this study is straightforward to state, though it has significant implications: AI does not independently drive employee engagement. It mediates — it amplifies, focuses, or redirects the engagement-shaping effects that organizational culture already exerts. This means that deploying AI engagement tools into a culturally dysfunctional organization is unlikely to work, and may actively make things worse by introducing new forms of algorithmic surveillance into environments already characterized by low trust.

The three mediation channels identified in this paper offer a structured way to think about this. AI enhances meaningfulness by enabling more personalized, purpose-aligned work experiences that deepen employees' sense of contribution. AI enhances psychological safety when it delivers fair, transparent, and responsive HR interactions that reduce anxiety about how data about employees is being used. And AI enhances resource availability by automating administrative load and optimizing workload distribution, giving employees the cognitive and emotional bandwidth to engage more fully with meaningful work. All three channels, crucially, require an underlying cultural substrate to function: a culture of innovation enables personalization; a culture of transparency enables safety; a culture of genuine care enables the wellness applications that free up availability.

The Saturation Finding and Its Implications

The Gaussian lifecycle analysis (R^2=0.961, peak 2025, K=263) carries a specific message for researchers: the field as currently framed is full. The conceptual space staked out by the existing 260 papers — culture predicts engagement; AI mediates this; trust moderates it — has been mapped. The next generation of contributions will need to move the conversation rather than continue it. The bibliometric data suggest several directions where the field has high centrality but low density: DEI dimensions of AI-HRM; longitudinal designs; ethical AI in the context of engagement; and geographic contexts beyond the Anglophone world and India.

Practical Implications

For HR leaders and organizational practitioners, the study yields five concrete guidance points. First, conduct a cultural readiness assessment before deploying AI engagement tools — not as a formality, but as a genuine diagnostic. The conditional nature of AI's mediating effect means that AI investment in the wrong cultural environment is not just ineffective but potentially harmful to engagement. Second, build trust before deploying algorithms. This means being transparent about how AI systems work, what data they use, and what decisions they influence. It means giving employees genuine agency over AI wellness tools. It means involving employees in co-designing AI-enabled HR processes, not just rolling out vendor solutions.

Third, treat leadership development as part of AI adoption strategy. The research is consistent on this point: leaders who model openness to AI, communicate clearly about digital change, and create psychologically safe environments for experimentation unlock the culture-AI-engagement pathway. Leaders who do not, close it. Fourth, prioritize AI wellness applications as engagement investments, especially for hybrid and remote teams where the human connection that sustains engagement is structurally harder to maintain. Fifth, customize AI tools to fit the cultural context in which they operate. An AI engagement tool calibrated for a flat, individualistic, low power-distance organizational culture may perform poorly — or actively backfire — in a hierarchical, collectivist one.

LIMITATIONS

This study has limitations that should be kept in mind when reading its findings. First, the secondary data design cannot access the granular, context-specific information that primary research would yield. The 51 included studies operationalize "organizational culture", "AI adoption", and "employee engagement" in different ways, making precise comparisons difficult and limiting the specificity of conclusions. Second, publication bias is likely present: studies reporting positive effects of AI on engagement are more likely to be published than those reporting null or negative results, which means the evidence synthesis probably overstates the positive case. Third, despite India's growing presence in the dataset, the literature remains predominantly English-language and relatively concentrated in certain cultural contexts, which limits the generalizability of the thematic findings. Fourth, the absence of formal meta-analysis means that effect sizes cannot be estimated, and the strength of hypothesized relationships can be supported directionally but not quantified. Fifth, nearly all included studies are cross-sectional, which means the dynamic, longitudinal character of the culture-AI-engagement relationship remains poorly understood.

SCOPE FOR FUTURE RESEARCH

The saturation of the current research framing opens rather than closes the door for future work. Several directions stand out as both theoretically important and practically feasible.

The most pressing need is for primary empirical testing of the triadic mediation model. Structural equation modeling (SEM) with primary survey data collected across multiple industries and geographies would provide the direct tests that the existing literature lacks. A particularly valuable design would include longitudinal measurement of culture, AI adoption, and engagement at multiple time points, to capture the feedback loops that cross-sectional data cannot see.

Cross-cultural studies remain underdeveloped. The culture-AI-engagement relationship almost certainly operates differently in high power-distance, collectivist contexts (much of Southeast Asia, parts of Africa and Latin America) than in the low power-distance, individualistic contexts where most existing research has been conducted. Studies that explicitly examine these moderating cultural dimensions would significantly expand the practical applicability of the triadic model.

The ethical dimensions of AI-mediated engagement management deserve their own research stream. Under what conditions do employees experience AI wellness monitoring as supportive rather than surveillance? How do transparency disclosures about AI data use affect engagement outcomes? Does involving employees in co-designing AI tools change their perceptions of organizational fairness? These are answerable empirical questions with direct implications for practice.

Finally, meta-analytic research that synthesizes effect sizes across the existing 51+ studies would substantially strengthen the evidential basis for the theoretical model. A formal meta-analysis with funnel plot analysis would also provide an honest assessment of publication bias — a limitation that this study can acknowledge but not remedy.

CONCLUSION

This paper began with a simple question: does organizational culture influence employee engagement through the lens of AI? The answer that emerges from synthesizing 51 peer-reviewed studies across a decade of scholarship is both affirmative and nuanced. Yes, culture shapes engagement — this is among the most robust findings in the management literature. Yes, AI adoption tends to strengthen engagement — but only when the cultural conditions are right. And yes, AI mediates the culture-to-engagement pathway in specific, identifiable ways: by enhancing meaningfulness, by strengthening psychological safety, and by freeing up the personal resources employees need to engage fully.

The bibliometric portrait of this field is equally instructive. The domain grew explosively, peaked in 2025, and has reached 99% saturation under its current framing. India has displaced Western nations as the leading contributor, reflecting the real-world convergence of AI adoption and workforce management challenges in the world's largest IT services ecosystem. The keyword landscape is dominated by "knowledge management" — a conceptual reminder that the AI-HRM relationship is, at its core, about how organizations know their people and use that knowledge well.

The practical message for organizations is clear: AI is not an engagement solution. It is a cultural amplifier. Organizations that invest in building innovation-oriented, psychologically safe, transparent cultures — and then deploy AI thoughtfully within those cultures — will find that technology genuinely deepens engagement. Organizations that reach for AI as a shortcut to engagement, without doing the harder cultural work first, are likely to be disappointed. The technology will surface the culture, for better or worse, at scale.

REFERENCES

Alzeiby, E. A., Islam, N., Shaik, A. S., & Yaqub, M. Z. (2025). AI adoption in enterprises for enhanced strategic human resource management practices: Benefiting the employee engagement and experience. Journal of Enterprise Information Management. https://doi.org/10.1108/jeim-05-2024-0249

Aulia, S. R., & Lin, W.-S. (2024). Embracing the digital shift: Leveraging AI to foster employee well-being and engagement in remote workplace settings in the Asia Pacific region. Asia Pacific Management Review. https://doi.org/10.1016/j.apmrv.2024.12.003

Bakker, A. B., & Demerouti, E. (2008). Towards a model of work engagement. Career Development International, 13(3), 209–223.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Bilan, S., Šuleř, P., Skrynnyk, O., Krajňáková, E., & Vasilyeva, T. (2022). Systematic bibliometric review of artificial intelligence technology in organizational management, development, change and culture. Business: Theory and Practice. https://doi.org/10.3846/btp.2022.13204

Blau, P. M. (1964). Exchange and power in social life. Wiley.

Divya, D., Jain, R., Chetty, P., & Siwach, V. (2024). The mediating effect of leadership in artificial intelligence success for employee engagement. Management Decision, 62(4), 1134–1158.

Dutta, D., & Mishra, S. K. (2024). Artificial intelligence-based virtual assistant and employee engagement: An empirical investigation. Personnel Review. https://doi.org/10.1108/pr-03-2023-0263

Hughes, C., Robert, L., Frady, K. K., & Arroyos, A. (2019). Artificial intelligence, employee engagement, fairness, and job outcomes. In Managing Technology and Middle- and Low-Skilled Employees. Emerald Publishing Limited. https://doi.org/10.1108/978-1-78973-077-720191005

Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. Academy of Management Journal, 33(4), 692–724.

Majumder, S., & Dey, N. (2025). AI in workplace wellness programs. Studies in Computational Intelligence, 1095, 218–240.

Marimón, F., Mas-Machuca, M., & Akhmedjanova, A. (2024). Trusting in generative AI: Catalyst for employee performance and engagement in the workplace. International Journal of Human-Computer Interaction, 40(18), 5022–5038.

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. International Journal of Human Resource Management, 28(1), 3–26.

Minbaeva, D. B. (2021). Disrupting HRM: AI and people analytics. Human Resource Management Review, 31(4), 100677.

Mittal, P., Jora, R. B., Sodhi, K. K., & Saxena, P. (2023). A review of the role of artificial intelligence in employee engagement. 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS). IEEE. https://doi.org/10.1109/icaccs57279.2023.10112957

Murire, O. (2024). Artificial intelligence and its role in shaping organizational work practices and culture. Administrative Sciences, 14(5), 92. https://doi.org/10.3390/admsci14050092

Navarro, C., Pulido-Martos, M., & Pérez-Lozano, C. (2024). The study of engagement at work from the artificial intelligence perspective: A systematic review. Expert Systems, 41(4), e13524.

Prentice, C., Wong, I., & Lin, Z. (2023). Artificial intelligence as a boundary-crossing object for employee engagement and performance. Journal of Retailing and Consumer Services, 73, 103361.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210.

Rožman, M., Tominc, P., & Milfelner, B. (2023). Maximizing employee engagement through artificial intelligent organizational culture in the context of leadership and training of employees: Testing linear and non-linear relationships. Cogent Business & Management. https://doi.org/10.1080/23311975.2023.2248732

Saks, A. M. (2006). Antecedents and consequences of employee engagement. Journal of Managerial Psychology, 21(7), 600–619.

Sari, R. E., Min, S., Purwoko, H., Furinto, A., & Tamara, D. (2020). Artificial intelligence for a better employee engagement. International Research Journal of Business Studies, 13(2), 173–188.

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. Journal of Happiness Studies, 3(1), 71–92.

Schein, E. H. (2010). Organizational culture and leadership (4th ed.). Jossey-Bass.

Shokrollahi, M. A. (2025). Studying the role of organizational culture and artificial intelligence integration in business performance. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5361971

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. Academy of Management Annals, 13(2), 535–550.

Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. Strategic HR Review, 17(5), 255–258.

Table 1: PRISMA 2020 Literature Selection Summary

Stage	Description	Records
Identification	Records retrieved from Google Scholar (198) and Litmaps (114)	n = 312
Duplicate Removal	Duplicate records removed	n = 260 (−52)
Title/Abstract Screening	Screened for relevance to core constructs; irrelevant records excluded	n = 150 (−110)
Full-Text Eligibility	Full-text assessed; non-HR/non-AI/quality concerns excluded	n = 65 (−85)
Final Inclusion	Detailed assessment; final analytical sample selected	n = 51 (−14)

Table 2: Summary of Hypotheses and Evidence Synthesis Results

H	Hypothesis	Key Evidence	Verdict
H1	Culture → Engagement (positive)	Kahn (1990); Saks (2006); Bley et al. (2022); Shokrollahi (2025); Murire (2024)	Supported — consistent evidence across diverse organizational and cultural contexts
H2	AI Adoption → Engagement (positive)	Mittal et al. (2023); Dutta & Mishra (2024); Marimón et al. (2024); Aulia & Lin (2024)	Supported — positive, conditional on cultural receptivity, trust, and implementation quality
H3	AI mediates Culture → Engagement	Alzeiby et al. (2025); Navarro et al. (2024); Divya et al. (2024); Raisch & Krakowski (2021)	Supported — convergent indirect evidence; no single study tests the full model directly
H4	Cultural readiness moderates AI's mediating effect	Shokrollahi (2025); Bley et al. (2022); Alzeiby et al. (2025)	Supported with qualification — no direct empirical tests of moderated mediation yet published

Source: Evidence synthesis across 51 peer-reviewed studies, 2017–2026

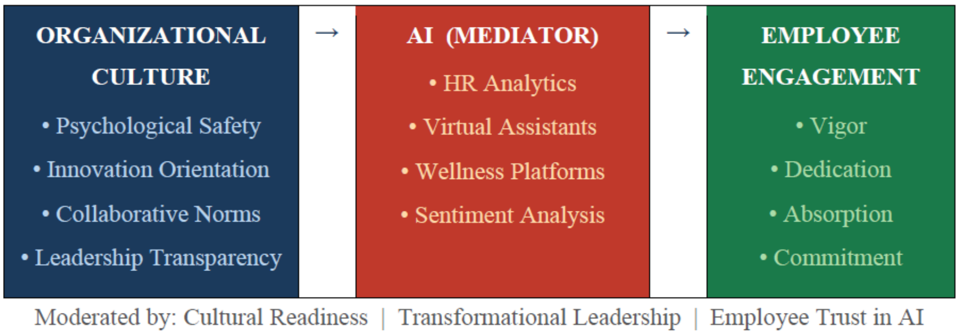

Figure 1: Theoretical Model — AI as Conditional Mediator in the Culture-Engagement Relationship

Figure 2: Bibliometric Overview Dashboard (Biblioshiny Analysis, 2017–2026)

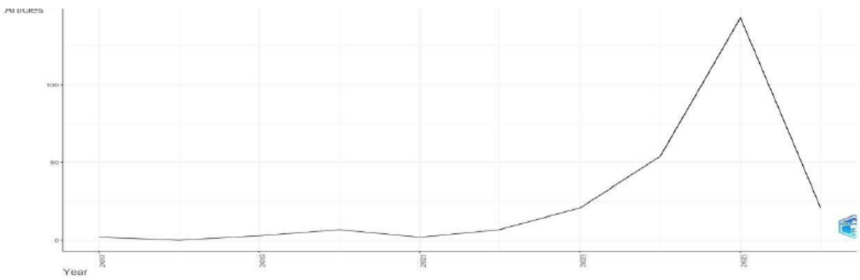

Figure 3: Annual Scientific Production Trend (2017–2026)

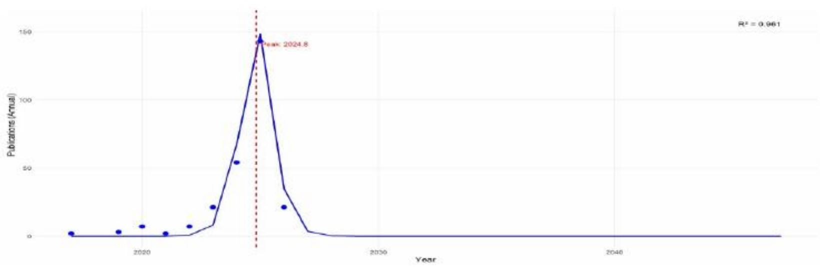

Figure 4: Research Lifecycle — Annual Publications with Gaussian Model Fit (R^2=0.961)

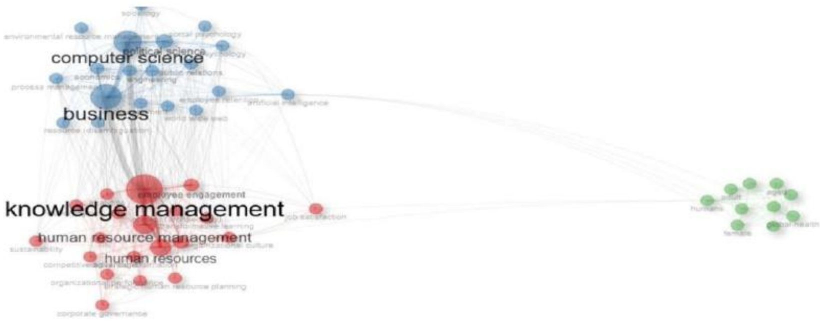

Figure 5: Keyword Co-occurrence Network — Three Thematic Clusters

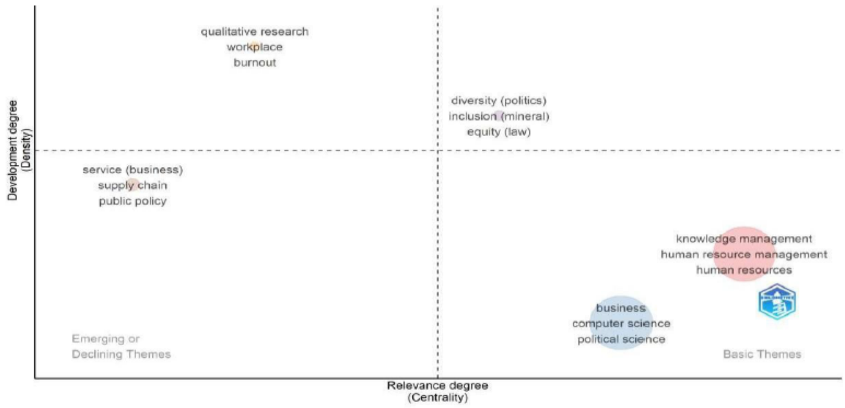

Figure 6: Thematic Map — Centrality vs. Development Density