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Artificial Intelligence, Employee Performance, and Career Development: A Mechanism-Based Systematic Review and Integrative Framework

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Abstract

Workplace adoption of artificial intelligence (AI) has accelerated sharply, yet research examines its effects on employee performance and on career development separately, leaving the connecting mechanisms unmapped. This study synthesizes how AI shapes both outcomes simultaneously and the conditions governing the direction of its effects. Following PRISMA 2020 and combining the CIMO and PEO frameworks, a Scopus search retrieved 195 documents, of which 63 studies (2019–2025; 6,889 respondents) met eligibility and quality-appraisal criteria (JBI; ROBIS); findings were integrated through thematic synthesis. The literature proves data-rich but framework-poor: 81.0% of studies lack an explicit theoretical anchor and 71.4% treat AI as monolithic. Four performance pathways (skill enhancement, motivational, knowledge augmentation, stress–threat) and three career-pathway clusters emerge, with trust in AI, AI literacy, and supervisory support determining whether AI augments or disrupts; the same exposure can produce opposite effects. The study proposes a provisional integrative framework linking the two domains through career adaptability and outlines six priority research directions for HRM theory, practice, and policy in developing economies.

Keywords artificial intelligence; employee performance; career development; systematic literature review; career adaptability

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1. INTRODUCTION

Workplace adoption of artificial intelligence (AI) has shifted from a contested prospect to an unavoidable operational reality: 82.5% of all scholarly publications on AI and employee outcomes over the past six years appeared in 2024–2025 alone. Beneath this volume, the literature has developed along two separate tracks. One examines how AI affects employee performance; the other how AI reshapes careers. The two rarely meet. In organizational practice, by contrast, an AI-adoption decision lands on both dimensions at once: what employees do today, and where their careers move over the long term.

This fragmentation reflects a deeper conceptual limitation. Most studies treat AI as a single stimulus whose effects can be measured independently on each outcome, overlooking one fact: the

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mechanism linking AI to performance and the mechanism linking it to career development operate through the same individual resources—competence, trust, motivation, and adaptive capacity. Separating the two dimensions forfeits the most consequential part of the phenomenon. This review addresses that gap by synthesizing the empirical evidence on the mechanisms through which AI drives change in both employee performance and careers, producing outcomes that vary with the contextual conditions surrounding it.

Two conditions create the need for an integrated synthesis. First, the existing volume of research is now sufficient to synthesize, yet it has never been brought together across the two outcome domains: studies on performance identify competence enhancement, motivation, knowledge expansion, and psychological threat, while studies on careers document reskilling pressures, trajectory shifts, and career adaptability—but no review reads the two tracks together to determine whether these mechanisms reinforce or conflict. Second, the moderating conditions that determine the direction of AI's effects have not been mapped in an integrated way. Trust in AI, AI literacy, and supervisory support are not mere control variables; they determine whether AI exposure produces augmentation or disruption, and that cannot be established from studies examining performance or careers in isolation.

Two prior reviews define the immediate boundary against which this study is positioned. Pandya and Wang (2024) scoped AI and career development but did not integrate performance, apply PRISMA 2020, or conduct quality appraisal. Bankins et al. (2024) examined AI across career stages but focused on career phases rather than the mechanisms operationalizing AI's influence. Others map AI across HRM or HRD broadly (Benabou & Touhami, 2025) without integrating performance and career mechanisms. No review has mapped how AI operates simultaneously on both outcomes, nor built a framework connecting them. Five gaps follow: the absence of integration of performance and career constructs in one analytic framework; the absence of mechanism-level analysis identifying processes rather than associations; a geographic imbalance marginalizing Southeast Asian and Global South contexts; the treatment of AI as monolithic by 71.4% of studies, without distinguishing automation, algorithmic management, and generative AI; and the near-total absence of longitudinal designs.

Four research questions organize this review, combining the CIMO framework (Context–Intervention–Mechanism–Outcome) for the mechanism-focused questions and PEO (Population–Exposure–Outcome) for bibliometric mapping. **RQ1:** How has research on AI, employee performance, and career development developed between 2019 and 2025 in temporal, methodological, theoretical, and geographic terms? **RQ2:** Through which mechanisms does AI affect employee performance, and which contextual conditions moderate them? **RQ3:** How does AI exposure reshape career-development pathways and competencies, and do effects vary by context? **RQ4:** What research gaps, limitations, and priorities can be identified from the 2019–2025 corpus?

The review contributes on four levels. Theoretically, it integrates employee performance and career development within a single mechanism-based framework, yielding an empirically testable provisional framework. Methodologically, the full PRISMA 2020 protocol with two-level quality appraisal (JBI Checklists; ROBIS), not applied in earlier reviews, yields a documented and replicable corpus. Empirically, mapping four performance-mechanism pathways and three career-pathway clusters with their moderators provides a directly usable evidence base. Geographically, it documents systematic differences in mechanisms across developmental contexts, with implications for labor policy in developing countries. Section 2 describes the methods; Section 3 presents results by RQ; Section 4 interprets findings, proposes the framework, and concludes.

2. METHODS

2.1. Review Design and Protocol

This systematic literature review (SLR) was designed and conducted in accordance with the PRISMA 2020 reporting guidelines (Page et al., 2021). The selection framework combines CIMO (Context–Intervention–Mechanism–Outcome) to structure the mechanism-focused questions with PEO (Population–Exposure–Outcome) to operationalize eligibility. This combination suits an interdisciplinary topic spanning human resource management (HRM), information systems (IS), and organizational behavior. Protocol documentation preceded the search, consistent with PRISMA 2020 item 2. The synthesis applies two complementary methods: descriptive bibliometric analysis for RQ1, and thematic synthesis following Thomas and Harden (2008) for RQ2 and RQ3, which reconstructs mechanism pathways not visible when studies are read in isolation.

2.2. Information Sources and Search Strategy

Scopus was the single retrieval database, chosen for its comprehensive indexing of the HRM–IS–organizational-behavior intersection in the post-2019 period (Martín-Martín et al., 2021) and its 70–80% document overlap with Web of Science for management topics, which limits the incremental gains of multi-database retrieval (Donthu et al., 2021; Singh et al., 2021). The single-database choice is acknowledged as a limitation in Section 3.8.

The search string combined three mandatory blocks linked by AND, so every record contained at least one term from each: Block A (AI as intervention; 34 terms, from “generative AI” and “algorithmic management” to “Industry 4.0”), Block B (employee performance; 26 terms covering in-role and extra-role constructs), and Block C (career development; 40 terms spanning competence and trajectory constructs). The full string appears in Appendix A. The token “AI” was excluded because, under TITLE-ABS-KEY, it retrieves large volumes of irrelevant material (e.g., avian influenza, artificial insemination). Filters restricted retrieval to articles and reviews (2019–2025, English). The 2019 cutoff reflects when workplace-AI research began treating AI as an operationalizable mechanism rather than a metaphor. The search returned 195 documents (180 articles, 15 reviews).

2.3. Eligibility and Study Selection

Eligibility was operationalized through an inclusion/exclusion matrix derived from CIMO-PEO (Appendix A). Studies had to examine an AI-based intervention in an organizational work context, involve employees in paid work, and report at least one measurable performance or career outcome. Excluded were unverifiable non-peer-reviewed journals, student/educational and clinical settings, and purely technical computer-science work without an organizational lens. Conference papers were excluded as a retrieval consideration, not a quality judgment. At any screening ambiguity, the default was tentative inclusion, consistent with the Cochrane Handbook (Higgins et al., 2023).

Of 195 documents (no duplicates, given the single-database search), 91 were excluded at title-and-abstract screening, leaving 104 sought for retrieval; 6 could not be obtained, and 98 were assessed in full, with 35 excluded. The final synthesis corpus comprised 63 studies. Borderline cases were resolved through structured re-assessment against criterion codes. The process is visualized in Figure 1.

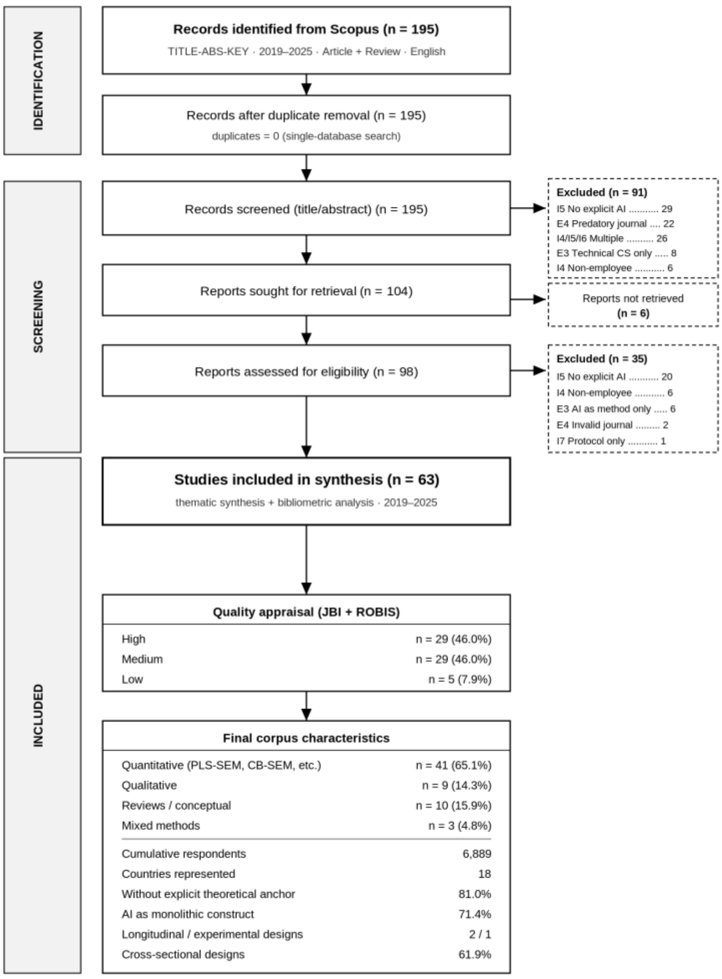

Figure 1. PRISMA 2020 flow diagram for study selection (Scopus, 2019–2025).

2.4. Quality Appraisal, Extraction, and Synthesis

Quality was appraised with the JBI Critical Appraisal Checklists (Aromataris & Munn, 2020) for empirical studies and ROBIS (Whiting et al., 2016) for reviews. Rather than excluding on a threshold, ratings stratified analytic weight: high-quality studies (n = 29; 46.0%) anchor the synthesis, medium-quality studies (n = 29; 46.0%) corroborate, and low-quality studies (n = 5; 7.9%) document the range of findings without serving as primary support. A binary cutoff would have removed 34 studies containing substantive observations, particularly from rarely represented contexts.

Data extraction used a standardized template covering bibliographic identity, study characteristics, substantive constructs (AI type, performance and career outcomes, mediators, moderators, theoretical framework), findings, and per-RQ relevance and quality ratings. Results are reported in four layers matching the RQs. Meta-analysis was not conducted: only 19 of 63 studies reported numeric sample sizes, and the diversity of AI constructs, outcome measures, and designs renders effect-size pooling indefensible. Thematic synthesis proceeded in three stages—line-by-line coding, descriptive themes, and analytic themes—with interpretive claims beyond individual studies permitted only at the third stage.

3. FINDINGS AND DISCUSSION

3.1. Corpus Overview

The final corpus of 63 studies spans 2019–2025, concentrated in 2024 (n = 16) and 2025 (n = 36)—82.5% in the final two years—driven by the mainstreaming of large language models since late 2022. Quantitative studies dominate (n = 41; 65.1%), followed by reviews (n = 10; 15.9%), qualitative (n = 9; 14.3%), and mixed-methods (n = 3; 4.8%). The 19 studies reporting sample sizes total 6,889 respondents (range 32–1,606; mean 363); total citations reach 1,500 (mean 23.8; maximum 316). Quality appraisal classified 29 studies as high, 29 medium, and 5 low. The synthesis rests primarily on high-quality studies, with medium-quality studies as corroborating evidence.

3.2. RQ1: Bibliometric Trends (2019–2025)

Publication output reveals three phases (Table 1): a latent phase (2019–2021; n = 2) characterizing AI as a disruptive HRM force without isolating mechanisms; a transitional phase (2022–2023; n = 9) examining specific constructs such as Industry 4.0 and algorithmic management; and an acceleration phase (2024–2025; n = 52) coinciding with mass adoption of generative-AI tools.

Table 1. Temporal Distribution of Publications (2019–2025)

Year	n	%	Phase
2019	1	1.6%	Latent
2020	1	1.6%	Latent
2021	0	0.0%	Latent
2022	5	7.9%	Transitional
2023	4	6.3%	Transitional
2024	16	25.4%	Acceleration
2025	36	57.1%	Acceleration
Total	63	100%	

Note: Latent phase (2019–2021) n = 2 (3.2%); transitional (2022–2023) n = 9 (14.3%); acceleration (2024–2025) n = 52 (82.5%).

Methodologically (Table 2), quantitative designs dominate, led by PLS-SEM and CB-SEM. Most striking is the scarcity of longitudinal (n = 2) and experimental (n = 1) designs against the dominance of cross-sectional surveys (n = 39; 61.9%)—a structural feature with a direct consequence: the mediation claims reported throughout the corpus cannot technically be interpreted as causal mechanisms.

Table 2. Distribution of Research Designs and Methods

Research Method	n	%
Quantitative, PLS-SEM	12	19.0%
Quantitative, survey (non-SEM)	11	17.5%
Quantitative, CB-SEM	10	15.9%
Qualitative	9	14.3%
Quantitative, cross-sectional survey	6	9.5%
Systematic review / meta-analysis	5	7.9%
Literature review	2	3.2%
Mixed methods	3	4.8%
Quantitative, longitudinal	2	3.2%
Experimental / quasi-experimental	1	1.6%
Total	63	100%

Note: Quantitative total n = 41 (65.1%), of which cross-sectional n = 39 (61.9%), longitudinal n = 2 (3.2%), experimental n = 1 (1.6%); qualitative n = 9 (14.3%); reviews n = 10 (15.9%); mixed methods n = 3 (4.8%).

Theoretically, only 12 studies (19.0%) explicitly named and operationalized a framework—most often socio-technical systems theory and the Job Demands–Resources (JD-R) model, followed by Career Construction, Conservation of Resources, Social Cognitive, P-E Fit, Self-Determination, and Protean Career theories. The remaining 81.0% operate without an explicit anchor, a cumulative limitation that makes findings difficult to compare, integrate, or extrapolate.

Geographically (Table 3), Asia dominates—India, China, Saudi Arabia, Indonesia, Pakistan, and Malaysia are the most productive contexts—followed by Europe and North America, while sub-Saharan Africa and Latin America are severely underrepresented. This breadth conceals a deeper imbalance:

most Global South studies rely on single-country cross-sectional designs without cross-national comparison, so the diversity of contexts is not matched by a diversity of theoretical perspectives.

Table 3. Geographic Distribution of Studies

Country / Region	n	%	Region
India	10	15.9%	South Asia
China	9	14.3%	East Asia
Saudi Arabia	5	7.9%	Middle East
United States	5	7.9%	North America
Indonesia	4	6.3%	Southeast Asia
Pakistan	4	6.3%	South Asia
Malaysia	4	6.3%	Southeast Asia
United Kingdom	4	6.3%	Europe
South Korea	3	4.8%	East Asia
Italy	3	4.8%	Europe
Germany	2	3.2%	Europe
Türkiye	2	3.2%	Europe / Middle East
Spain	2	3.2%	Europe
Jordan	1	1.6%	Middle East
Egypt	1	1.6%	North Africa
Ghana	1	1.6%	Sub-Saharan Africa
Morocco	1	1.6%	North Africa
Uzbekistan	1	1.6%	Central Asia
Not specified	10	15.9%	—

Note: Some studies span more than one country context, so total context entries exceed 63 studies. Roughly 18 countries are represented. Asia dominates the corpus.

Most studies treat AI as a monolithic construct: generic "artificial intelligence" dominates (n = 45; 71.4%), with more specific designations far rarer (Table 4). Algorithmic management—the most direct operationalization of AI as an active managerial mechanism—appears in only one study, an absence disproportionate to its prevalence in logistics, retail, and platform work.

Table 4. Frequency of AI Types Examined

AI Type	n	%
Artificial intelligence (generic / monolithic)	45	71.4%
Digital transformation	13	20.6%
AI adoption	12	19.0%
Automation	8	12.7%
Machine learning	6	9.5%
Industry 4.0 technologies	5	7.9%
Generative AI / LLM	5	7.9%
Algorithmic management	1	1.6%

Note: Frequencies are non-exclusive, a single study may name more than one AI type, so the total exceeds 63.

3.3. RQ2: Mechanisms Affecting Employee Performance

Analysis of 37 high-relevance studies, supplemented by 18 of medium relevance, reveals four mechanism pathways (Table 5). The central finding is that AI's effect on performance is conditional: the same mechanism can raise or lower performance depending on the moderating conditions present.

Table 5. Mechanistic Pathways of AI on Employee Performance (RQ2)

Pathway	n Studies	Key Mediators	Critical Moderators	Direction of Effect
Skill & Competency Enhancement	39	AI self-efficacy; AI competence	AI literacy; trust in AI	Positive (conditional)
Motivational	27	Work engagement; job satisfaction	Supervisory support; organizational culture	Positive / negative (appraisal-dependent)
Knowledge Augmentation	27	Knowledge sharing; organizational learning	Trust in AI; digital autonomy	Positive (conditional)
Stress & Threat	17	AI anxiety; job insecurity; technostress	AI literacy; trust in AI	Negative (reversible)

Note: The total exceeds 63 because a single study may identify more than one pathway. The most consistent cross-pathway moderators are trust in AI (12 studies), AI literacy (11 studies), and supervisory support (9 studies).

Skill and competency enhancement (n = 39) is the most widely supported mechanism: AI exposure drives competence development as the intervening condition linking AI to improved performance. Priatna et al. (2025) show machine-learning-based production raising digital competence alongside performance gains; Kumar and Mittal (2024) find employee learning—not exposure per se—the proximal driver, mediating trust in AI and human–AI collaboration; Chen et al. (2025) show generative-AI integration activating knowledge-sharing through AI self-efficacy, moderated by technical literacy and growth mindset. Wotschack et al. (2023), the corpus's only experiment, show AI-assisted training accelerating skill acquisition especially for underrepresented workers, suggesting AI can reduce structural learning inequality. Convergent evidence across manufacturing, service, and cross-industry settings reports the same competence-to-performance link (Pawenary et al., 2025; Subramaniam et al., 2025; Vasilidou et al., 2025; Venugopal et al., 2024; Xin et al., 2022; Yunianto et al., 2025).

The motivational pathway (n = 27) operates through work engagement, satisfaction, and related attitudes. Rožman et al. (2022) establish that AI-supported talent-management practices predict work engagement, which drives performance; Bastida et al. (2025) position engagement as the central mediator between AI in HRM and organizational resilience. The pathway is not uniformly positive: Başer et al. (2025) show that awareness of automation (STARA awareness) suppresses engagement when perceived as a threat. The same exposure can thus activate or suppress motivation depending on how employees interpret the technology (Bawazir et al., 2025; Toumia & Yetgin, 2025).

Knowledge augmentation (n = 27) treats AI as infrastructure for collective knowledge creation, sharing, and learning. Zhou et al. (2024) show trust in AI converting AI-related stress into active learning; Chen et al. (2025) find skill-threat perception paradoxically activating knowledge-sharing through AI self-efficacy as a compensatory coping strategy—a mechanism rarely theorized previously. Related work links AI exposure to creativity and innovative work behavior, conditioned by digital literacy or AI's own limitations (Caroline et al., 2025; Hussain & Rehman, 2025; Jiang et al., 2022; Zirar, 2023).

The stress-and-threat pathway (n = 17) produces predominantly negative effects that can reverse with individual and organizational moderators. Malik et al. (2022) document information-security fears, privacy concerns, and job insecurity systematically undermining performance; Dhilipan et al. (2025), the corpus's largest survey (n = 1,606), confirm AI anxiety simultaneously depressing performance, well-being, and career prospects. Ding et al. (2025) reveal AI's dual-process nature within a single study: exposure simultaneously raises competence and depletes emotional resources through exhaustion, with AI literacy as the boundary condition—showing the net effect cannot be predicted from exposure intensity alone. The pathway also runs through job-insecurity and fairness concerns (Chung et al., 2025; Majrashi, 2025; Tatiparti et al., 2025; Wadhwa et al., 2025).

Across all four pathways, three moderators recur. Trust in AI is the most critical dispositional moderator, strengthening the motivational and knowledge pathways while attenuating the threat pathway (Kong et al., 2023; Kumar & Mittal, 2024; Zhou et al., 2024). AI literacy is the boundary condition determining whether employees access the augmentative or disruptive version of the same exposure. Supervisory support and transformational leadership condition these effects organizationally (Hu et al., 2024; Odugbesan et al., 2023).

3.4. RQ3: Mechanisms Reshaping Career Development

Analysis of 36 high-relevance studies, supplemented by 23 of medium relevance, reveals three career-pathway clusters and four outcome domains (Table 6).

Table 6. Career-Pathway Clusters and Career-Development Outcome Domains (RQ3)

Career-Pathway Cluster	n Studies	Outcome Domain (corpus frequency)	Key Career Mediator	Dominant Geographic Context
Cluster 1: Reskilling–Upskilling Imperative	25	Reskilling/upskilling (9); lifelong learning (6); employability (3)	Career resilience; digital capability	South Asia; Middle East
Cluster 2: Career	15	Talent development (11);	Career	East Asia;

Adaptability as Central Mediator		HRD/professional (9); career adaptability (4)	adaptability; AI self-efficacy	Southeast Asia
Cluster 3: Dual Impact on Career Sustainability	8	Career sustainability (3); career trajectory (1)	Trust in AI; employee–AI collaboration	East Asia; multi-region

Note: Some studies contribute to more than one cluster. Figures in the outcome-domain column refer to the frequency of that outcome across the full corpus (n = 63).

Cluster 1: the reskilling and upskilling pressure (n = 25) is the most extensively documented career mechanism, generated by two simultaneous forces—displacement of existing competences through automation, and new demand for AI-augmented profiles. Agarwal et al. (2022) identify reskilling as the central HRM response to Industry 4.0 disruption in emerging economies; Alhusban et al. (2025) document a temporal mismatch in Jordan's financial sector between AI deployment and workforce readiness; Caratù et al. (2025) identify reskilling, professional development, and digital-capability building as the dominant HRM imperatives.

Cluster 2: career adaptability as the central mediator (n = 15). Career adaptability—an individual's readiness for managing career-development tasks—is the most consistent individual-level mediator between AI exposure and career outcomes. Kong et al. (2023; Journal of Vocational Behavior; 147 citations), the highest-impact study for this question, show employee–AI collaboration mediating trust in AI and career sustainability, with protean career orientation as moderator—establishing trust as the upstream determinant of whether AI collaboration yields long-term gains. Leong et al. (2025) confirm career adaptability mediating AI-driven conditions and work engagement; Burhan and Fatima (2025) confirm digital leadership activating adaptability through serial mediation of AI attitude and career resilience; Kumi et al. (2024) confirm the pattern in Ghana's public sector, showing it holds beyond Asian and Western contexts.

Cluster 3: dual impact on career sustainability (n = 8). Zhang and Chin (2024) establish career sustainability as a mediator between AI-based digitalization and innovative work behavior; Mohamud et al. (2025) show AI mediating individual characteristics and career sustainability only when remote-work arrangements are present—indicating the career-sustaining effect depends on structural work arrangements, not AI-use intensity alone.

Career-mechanism patterns differ by developmental context. South Asia emphasizes the reskilling-employability pathway, with AI anxiety the most documented barrier. Southeast Asia shows a dual pattern: AI enhances talent development in formal-sector organizations while worsening precarity for informal workers and SMEs. East Asia is most advanced, operationalizing career adaptability and sustainability as measured outcomes. In Africa and the Middle East, benefits concentrate in formal-sector and technology-based occupations (Upadhyay, 2025), with limited spillover. Across the high-relevance studies, four outcome domains recur: talent development (n = 11 Behera et al., 2025; Shakhshina et al., 2025), HRD and professional outcomes (n = 9 Khandelwal et al., 2024; McLean & González Ortiz de Zárate, 2024), reskilling/upskilling as end results (n = 9), and lifelong learning (n = 6 Ahn, 2024; Salvadorinho et al., 2024; Zervas & Stiakakis, 2025).

3.5. RQ4: Research Gaps and Agenda

Analysis of 17 high- or medium-relevance studies, combined with documented corpus limitations, reveals five systematic gaps (Table 7). Theoretical fragmentation is most fundamental: only 7 of 63 studies examine both outcome domains, and none integrates them within one framework. A deficit of longitudinal design and causal inference runs throughout—only two longitudinal (Guan et al., 2025; Nazeer & Ahmad, 2025) and one experimental study (Wotschack et al., 2023)—so causal direction cannot be established (Wahlström et al., 2024). The generative-AI and LLM lacuna is striking: despite the 2024–2025 concentration, only five studies treat generative AI as distinct from legacy automation. The near-absence of algorithmic-management research (one study) is disproportionate to its prevalence in platform, logistics, and service work. Finally, the marginalization of the Global South in theorization persists: studies replicate Western frameworks without engaging the institutional and labor-market conditions that differentiate non-Western contexts.

Table 7. Systematic Research Gaps and Research Agenda

No.	Systematic Gap	Evidence in Corpus	Proposed Research Priority
G1	Theoretical fragmentation; no integrative performance–career framework	Only 7/63 studies examine both outcome domains; none integrates them theoretically	Empirical studies testing the provisional integrative framework longitudinally
G2	Deficit of longitudinal design; cross-sectional dominance (61.9%)	Only 2 longitudinal and 1 experimental study in the entire corpus	Multi-wave longitudinal designs (min. 2 waves) to establish mechanism causality
G3	Generative-AI and LLM lacuna as a distinct construct	Only 5/63 studies examine generative AI/LLMs specifically	Empirical studies of the specific effects of LLM-based tools on performance and careers
G4	Near-absence of algorithmic-management research	Only 1/63 studies examines algorithmic management explicitly	Research on the nexus of algorithmic control, performance, and career autonomy
G5	Marginalization of the Global South in theorization	Africa and Latin America almost absent; existing studies replicate Western theory	Comparative studies across development levels; context-grounded theorization for emerging economies

Several methodological limitations recur and constrain the claims that can be drawn. Common-method bias is pervasive: most quantitative studies rely on single-source self-report without adequate controls. Construct validity is inconsistent, as “artificial intelligence” is operationalized from specific instruments to broad digitalization. Sample homogeneity is common—convenience samples from single organizations or countries. Publication bias toward positive findings is evident: no study reports a null or net-negative effect as a primary finding, even though qualitative evidence indicates negative effects occur.

3.6. Reading the Findings Across Research Questions and a Provisional Framework

The four questions were posed separately, but their answers are not independent. Read together, they show a field accumulating observations faster than understanding. The acceleration in RQ1 is real but uneven: volume has grown dramatically, yet 81.0% of studies lack a theoretical anchor and 71.4% treat AI as monolithic, so mechanisms attributed to AI cannot be compared systematically. RQ2's four pathways operate simultaneously, with trust in AI, AI literacy, and supervisory support determining whether each amplifies or reduces performance—requiring an analytic stance that treats AI's effect as inherently conditional. RQ3 extends the same conditionality to a longer horizon, with career adaptability the construct most consistently mediating the AI–career relationship (strongest support Kong et al., 2023). Its significance is that it links task-level consequences of AI adoption to long-term career consequences—the integration point grounding the framework below.

Drawing on relational patterns recurring across the corpus rather than any single study, AI is best modeled as an intervention operating through two parallel but connected pathways (Figure 2). The framework is provisional and should be treated as a testable proposition. The performance pathway runs from AI exposure through trust in AI and digital autonomy as threshold conditions, activating one or more of the four mechanisms, and then producing in-role and extra-role performance effects. The career pathway runs from AI exposure through career adaptability as the central mediator, producing reskilling-upskilling, career-sustainability, and talent-development outcomes. The two connect through an integration link: career adaptability and skill enhancement operate on overlapping individual resources and are likely bidirectional—a relationship not yet directly tested.

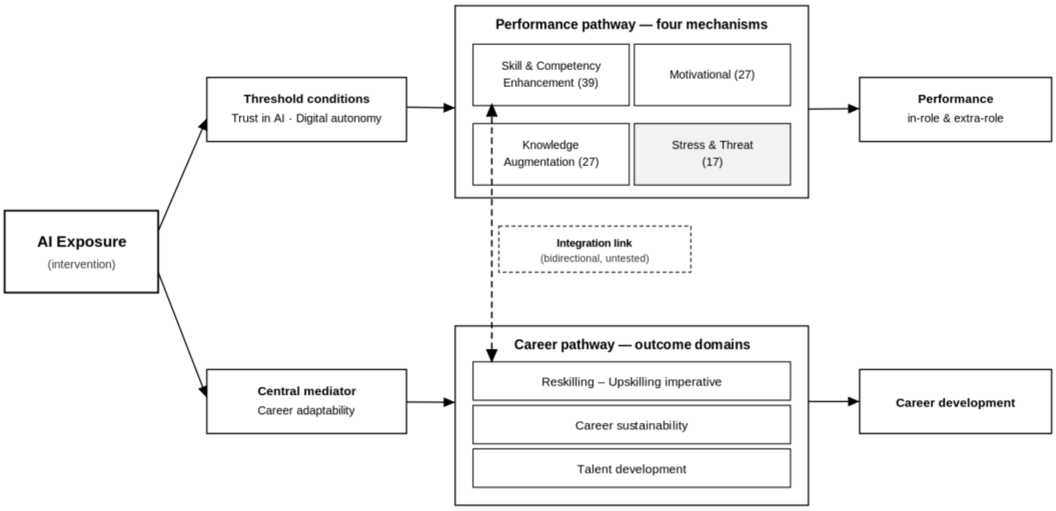

Figure 2. Provisional integrative framework: two parallel pathways (performance and career) linked through career adaptability.

Three implications follow: a study examining only the performance pathway loses the accumulating career consequences; one examining only the career pathway loses the immediate performance mechanisms that shape downstream outcomes; and one treating AI as a single construct aggregates across mechanisms that operate differently, reducing rather than improving precision.

3.7. Theoretical and Practical Implications

Three theoretical contributions follow. First, the conditionality of AI's effect should be a baseline assumption, not an added finding: the same AI produces augmentation in one context and disruption in another, with trust in AI, AI literacy, and supervisory support determining direction rather than merely magnitude. Studies measuring only direct AI-outcome relationships without operationalizing these conditions yield findings that cannot generalize. Second, the JD-R model requires calibration for the AI context: the same exposure can function as a resource that augments competence (Bastida et al., 2025; Rožman et al., 2022) or a demand that generates anxiety and monitoring pressure (Başer et al., 2025; Ding et al., 2025), so AI's resource-versus-demand status is contingent, not fixed. Third, career adaptability should be positioned as a bridging construct: the studies examining both domains consistently find it operating at their intersection, determining whether performance benefits convert into long-term career gains—while AI self-efficacy recurs as a mediator from competence through knowledge sharing to threat coping, strengthening Social Cognitive Theory (Chen et al., 2025; Kumar & Mittal, 2024).

Relative to prior reviews, this SLR confirms Pandya and Wang's (2024) finding that reskilling dominates the career response (corroborated by Cluster 1) while adding the performance dimension and PRISMA 2020 protocol they lacked; it extends Bankins et al. (2024) from career stages to operationalized mechanisms; and it extends Kong et al. (2023) by elevating trust in AI from a determinant of career sustainability to an integrative construct moderating the entire performance pathway.

For practice, AI literacy is the intervention point with the greatest leverage: it moderates the broadest set of pathways, reducing the threat mechanism while amplifying skill-enhancement and motivational pathways, and remains amenable to intervention while remediation is still feasible—so treating it as post-implementation remediation is a sequencing error. Integrating career-development programs with the AI-adoption roadmap is likewise not optional, since the same exposure event activates both pathways. For leaders, the temporal mismatch between AI deployment and workforce readiness is the most practically significant finding (Alhusban et al., 2025; Wahlström et al., 2024); building trust before implementation is supported across contexts (Kong et al., 2023; Zhou et al., 2024). For policymakers in developing countries, mechanisms identified in high-income settings cannot be assumed to hold without modification, and the career-sustainability risks of AI—especially from largely unstudied algorithmic management—are likely to fall most heavily on the least-represented contexts (Dhilipan et al., 2025).

3.8. Limitations

Three limitations constrain the conclusions. The restriction to Scopus as a single database, though defensible given its coverage and high convergence with alternatives (Martín-Martín et al., 2021; Singh et al., 2021), cannot rule out articles indexed exclusively elsewhere. The corpus's domination by cross-sectional designs means the mechanism pathways are supported by associational rather than causal evidence; the findings should be read as identifying plausible mechanisms and moderators, not confirming causality, with only two longitudinal and one experimental study providing stronger evidence for specific relationships. The restriction to English-language publications excludes local-language literature from Asia, Africa, and Latin America—precisely the perspective most needed for the geographic differentiation this review identifies as a priority.

4. CONCLUSION

This SLR synthesizes 63 studies (2019–2025; 6,889 respondents; ~18 countries) on how AI shapes employee performance and career development simultaneously, through which mechanisms, and under what conditions effects change direction. The field is data-rich but framework-poor: 82.5% of publications concentrate in 2024–2025, yet 81.0% lack an explicit theoretical anchor and 71.4% treat AI as generic. Four performance pathways (skill enhancement, motivational, knowledge augmentation, stress-threat) operate simultaneously, with trust in AI and AI literacy determining which version employees receive; career adaptability is the most consistent mediator linking task-level effects to long-term trajectories, and mechanism differentiation by developmental context is empirically confirmed. Five systematic gaps—theoretical fragmentation, a longitudinal-design deficit, the generative-AI lacuna, the near-absence of algorithmic-management research, and the marginalization of the Global South in theorization—are direct consequences of the design choices dominating the corpus and constrain the practical utility of its findings.

This review differs from Pandya and Wang (2024) by integrating performance and applying full PRISMA 2020 with two-level quality appraisal, and from Bankins et al. (2024) by its mechanistic focus on the processes through which AI's influence operates and changes direction. The provisional integrative framework is an empirically testable proposition, not a summary of existing literature; the corpus does not support a stronger claim. One message extends beyond the specific arguments: AI does not produce a single, averageable effect. It activates different mechanisms depending on who uses it, in what organization, under what leadership, and in which context of economic development. Without commensurate investment in AI literacy, supervisory readiness, and career-development infrastructure, the speed of AI adoption is a predictable way to convert the potential for augmentation into dysfunctional risk. Building six priorities—longitudinal and mixed-methods designs, disaggregation of generative AI, algorithmic-management research, cross-national comparison, integrated performance-career theorization, and attention to equity and inclusion (Marabelli & Lirio, 2025)—would move the field from descriptive mapping toward explanatory synthesis.

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