

Beyond Data Literacy: The Interpretive Competencies HR Professionals Need for AI-Augmented Performance Management in Sub-Saharan Africa

Jacob Patrick Belinga Bessala 

Applied Economics Management Laboratory (LEMA), Faculty of Economics and Applied Management, University of Douala, Douala, Cameroon

Email: jacob.belinga@outlook.com

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Abstract

Artificial intelligence (AI) now performs a large share of performance management (PM) work in organisations worldwide, yet the professionals responsible for governing these systems are widely reported to lack the skills to interpret what the algorithms produce. Industry frameworks respond by prescribing data literacy as the core AI-era competency, but this paper argues that data literacy is necessary and insufficient, and proposes a narrower, more precisely bounded construct to close the gap. Adopting an integrative literature review and conceptual framework design, with search-and-screening transparency limitations disclosed, the paper synthesises institutional theory, competence-in-action theory, algorithmic literacy scholarship, algorithmic-control theory and Ubuntu relational philosophy into a five-tradition architecture, illustrated by secondary evidence from Sub-Saharan Africa (SSA), including published empirical studies from South Africa and regional reviews, and contextualised through institutional data from the International Telecommunication Union and AfriCatalyst. It introduces algorithmic interpretive competence (AIC): the capacity of the HR professional responsible for governing an organisation's AI-augmented PM system to interpret, translate, mediate and contest algorithmic performance outputs. Five propositions with falsifiability clauses link AIC to procedural justice, interactional justice, and trust outcomes, with institutional voids and infrastructure constraints as moderators. The paper is the first to theorise a PM-specific, institutionally contextualised interpretive-competency construct for AI governance, offering a research and curriculum agenda for HR development in institutionally constrained settings.

Keywords

Algorithmic Interpretive Competence, AI-Augmented Performance Management, Institutional Voids, Sub-Saharan Africa, Data Literacy

1. Introduction

By the end of 2025, 95% of chief human resources officers (CHROs) reported having adopted artificial intelligence somewhere in their function, yet nearly three-quarters of HR leaders report only moderate or minimal returns from their AI investments (Gartner, 2026b). Performance management (PM) has been one of the principal beneficiaries of this diffusion: continuous monitoring dashboards, sentiment analysis, productivity scoring and automatically generated feedback have replaced or supplemented the annual appraisal in a growing share of firms. Yet the same data that record near-universal adoption record a starkly different picture of capability. Only 8% of HR leaders believe their managers have the skills to use AI effectively (Gartner, 2025a), and 88% of HR leaders report that their organisations have not realised significant business value from the AI tools they have deployed (Gartner, 2025b). Deloitte's most recent Global Human Capital Trends survey finds that 61% of managers and 72% of workers do not trust their organisation's PM process, and that only 26% of organisations consider their managers effective at enabling performance (Deloitte, 2025). A function that is being algorithmically transformed at scale is, on the evidence, being governed by professionals who are not equipped to interpret what the transformation produces.

This is not primarily a data literacy problem, although it is frequently framed as one. The Society for Human Resource Management (SHRM), the Chartered Institute of Personnel and Development (CIPD) and the Academy to Innovate HR (AIHR) each treat data literacy, defined broadly as the ability to read, understand and reason with data, as the central AI-era competency for HR professionals (Society for Human Resource Management, 2025; Chartered Institute of Personnel and Development, 2024; Van Vulpen & Veldsman, 2022). Deepa et al. (2024) extend this logic academically, mapping the managerial cognitive, human capital and social capital competencies that HR managers need to adopt AI across recruitment, learning and workforce planning. What these frameworks share is an assumption that algorithmic outputs are essentially transparent: once an HR professional can read a dashboard, the argument goes, the interpretive work is largely done. Evidence from performance management specifically suggests otherwise. Practitioner guidance from Worklytics (2025), a vendor document offering best-practice advice for incorporating AI usage into performance reviews, notes that organisations struggle to distinguish human capability from AI assistance when AI-generated content enters performance reviews. Tong et al. (2021) show experimentally that AI-generated feedback and human-communicated feedback pro-

duce different employee responses even when the underlying content is identical, because employees interpret the act of AI deployment, not only its output. Konjen (2025) and Liu et al. (2024) document that algorithmic systems systematically miss intangible contributions, creativity, collaborative problem-solving and contextual judgement, that data literacy alone does not equip a manager to recover. Reading a score is not the same as knowing what the score misses, what it should mean for an individual employee, or when it should be overridden.

The gap widens further once the institutional setting shifts from the contexts in which most AI-HRM scholarship has been produced. Much of Sub-Saharan Africa (SSA) presents a distinctive combination of conditions: internet penetration of only 38% against a global average of 68%, an urban-rural connectivity gap of 34 percentage points, and only 18% of countries reaching the most advanced tier of ICT regulatory maturity (International Telecommunication Union, 2025). Khanna and Palepu's (2010) concept of institutional voids, the absence of the specialised intermediaries, regulators and skills ecosystems that support market transactions in developed economies, describes much of this environment. In the less digitally developed SSA economies, no AI ethics board, well-resourced data protection authority or algorithmic auditing service stands between the HR professional and the algorithm; the professional must internalise functions that external institutions perform elsewhere. At the same time, Ubuntu-informed relational and communal norms of performance and dignity (Mangaliso, 2001; Mbiti, 1990) offer a normative resource, though not a universal empirical descriptor of all SSA workplaces, that sits in tension with individualistic, metric-driven algorithmic assessment, adding a cultural dimension that generic competency frameworks, built for Western or Asian enterprise contexts, do not anticipate.

The focal actor in this framework is the **HR professional responsible for governing an organisation's AI-augmented PM system**, typically an HR business partner, HR manager, or people analytics lead, rather than a CHRO (whose role is strategic oversight) or a line manager (whose role is day-to-day performance conversation). Where the paper draws on survey data about CHROs (e.g., Gartner's CHRO surveys) or about employees (e.g., Tong et al.'s field experiment), the actor surveyed is identified explicitly.

The scholarly response to this transformation has moved faster than the practitioner infrastructure needed to act on it. Budhwar et al. (2023) convened more than twenty HRM scholars to map the perspectives and research directions generative AI opens for the field, and Budhwar et al. (2022) had already catalogued the broader challenges and opportunities AI poses for international HRM. Chowdhury et al. (2024) propose a strategic HRM framework for generative AI specifically, while Chowdhury et al. (2023) develop an AI capability framework covering the competencies organisations, rather than individual professionals, require to extract value from AI in HRM. These contributions establish that the field recognises a capability problem. None isolates the performance management function,

and none asks what an individual HR professional, standing between an algorithm and an employee whose livelihood the algorithm partly governs, needs to be able to do in the moment of interpretation. That is the gap this paper addresses.

Three sub-gaps therefore converge. First, no competency framework addresses performance management specifically, as distinct from the recruitment- and learning-oriented focus of [Deepa et al. \(2024\)](#) and the assimilation-process focus of [Prikshat et al. \(2023\)](#). Second, no framework theorises the distance between what algorithmic PM systems produce and what HR professionals must do with that output, the algorithmic interpretive gap. Third, no framework accounts for how institutional voids, which vary considerably across the region's institutional tiers (Section 2.3), reshape competency requirements. This paper addresses the following research question: what interpretive competencies does the HR professional responsible for governing an AI-augmented performance management system require to produce PM outcomes that employees perceive as procedurally just, informationally transparent and interactionally dignifying, and how do institutional voids in the less institutionally developed parts of Sub-Saharan Africa shape these competency requirements beyond conventional data literacy?

Effective AI-augmented PM governance, as used in this paper, refers to the capacity of the responsible HR professional to produce PM outcomes that are procedurally just (employees perceive the process as fair), informationally transparent (employees understand the basis for evaluative decisions), and interactionally dignifying (feedback preserves the employee's sense of respect and agency). Decision validity (whether algorithmic ratings accurately reflect actual performance) is a distinct construct that this framework treats as a necessary antecedent, good governance requires technically valid outputs, but not as the outcome AIC is primarily designed to produce.

The paper makes three contributions. It introduces algorithmic interpretive competence (AIC), a construct defined as the contextual interpretation and professional judgement applied to algorithmic PM outputs, with technical-algorithmic literacy and ethical-regulatory knowledge as antecedents and organisational governance as an enabling condition. It develops a framework that maps AIC onto the stages of a canonical PM cycle (goal setting, continuous monitoring, appraisal, feedback delivery, pay and promotion decisions, and employee voice), thereby grounding the construct in specific governance tasks rather than abstract dimensional labels. It integrates institutional theory, competence-in-action theory, algorithmic literacy scholarship, algorithmic-control theory and Ubuntu relational philosophy in a five-tradition architecture in which each tradition passes an explicit parsimony test (Section 6.1), and illustrates the resulting propositions with secondary SSA evidence. The remainder of the paper proceeds as follows. Section 2 develops the theoretical foundations. Section 3 sets out the integrative review methodology. Section 4 presents the framework and its construct architecture. Section 5 states five falsifiable propositions. Section 6 discusses theoretical and practical implications, and Section 7 concludes.

2. Theoretical Foundations

2.1. AI-Augmented Performance Management: The New Metric Landscape

Performance management is undergoing a structural shift from periodic, effort-based appraisal towards continuous, outcome-based measurement. Where a manager once relied on an annual review conversation and a small number of subjectively weighted criteria, AI-augmented systems now generate productivity scores, sentiment readings, communication-pattern analyses and real-time feedback drawn from digital traces of work. The shift changes what the HR professional responsible for PM governance is asked to process: not a periodic narrative judgement but a continuous stream of quantified, algorithmically produced claims about employee performance. This transition has outpaced organisational trust. [Deloitte \(2025\)](#) finds that 61% of managers and 72% of workers distrust their organisation's PM process, and that managers spend approximately 40% of their time on administrative tasks against only 13% on developing people, leaving little capacity to interrogate what algorithmic outputs actually mean. A parallel and underappreciated complication is attribution. [Tong et al. \(2021\)](#) establish experimentally that employees respond differently to feedback depending on whether it is attributed to an algorithm or a human source, which extends naturally to a harder problem as generative AI becomes embedded in day-to-day work: separating an employee's own capability from AI assistance in the first place. Practitioner guidance from [Worklytics \(2025\)](#), a vendor document offering best-practice advice for the review cycle, corroborates that this attribution problem is already a live operational difficulty for evaluators, a problem that has no precedent in pre-AI performance measurement and for which existing appraisal criteria offer no guidance. [Konjen \(2025\)](#) adds that algorithmic systems, by design, capture what is countable: they miss intangible contributions such as informal mentoring, communal problem-solving and creative improvisation that do not leave a clean digital trace.

For the focal HR professional, this new metric landscape is not simply more data to read. It is a qualitatively different interpretive task at each stage of the PM cycle: judging which metrics the algorithm can and cannot capture during goal setting; detecting surveillance overreach during continuous monitoring; contextualising scores and recovering intangible contributions during appraisal and rating calibration; communicating algorithmic assessments with dignity during feedback delivery; exercising override judgement and detecting bias in high-stakes pay and promotion decisions; and facilitating meaningful employee challenge to algorithmic decisions during voice and appeal processes. [Deloitte's \(2024\)](#) preceding trends survey had already identified the redefinition of worker performance beyond narrow productivity metrics as a leading organisational priority. [Betterworks \(2026\)](#) reports that 90% of HR leaders say AI has redefined what counts as high performance, yet only 42% of organisations have updated their formal goal-setting processes to reflect that redefinition, and that a readiness gap separates

executives, 92% of whom feel ready to use AI, from employees, only 51% of whom share that confidence. The metric landscape, in other words, is changing faster than the organisational processes, and the professional capabilities, built to govern it.

2.2. The Algorithmic Interpretive Gap: Beyond Data Literacy

The dominant practitioner response to this shift has been to prescribe data literacy. SHRM's nine-competency Body of Applied Skills and Knowledge includes no AI-specific dimension (Society for Human Resource Management, 2025); CIPD's Profession Map treats technology as a single generic knowledge standard (Chartered Institute of Personnel and Development, 2024); and AIHR's T-shaped competency model places data literacy alongside business acumen and digital agility as one broad foundational layer rather than a performance-management-specific interpretive capacity (Van Vulpen & Veldsman, 2022). These frameworks are practitioner-derived and not explicitly theoretically grounded, a characteristic that limits their capacity to specify what competence means in a particular professional context. Academically, Deepa et al. (2024) offer the most rigorous treatment to date, mapping managerial cognitive capability, human capital and social capital competencies for AI adoption using the dynamic capabilities view, but their scope spans all HR functions rather than isolating the distinctive interpretive demands of performance management. Prikshat et al. (2023) integrate the technology-organisation-people framework with innovation assimilation theory to explain how AI-augmented HRM is adopted, diffused and routinised within organisations; their contribution addresses the assimilation process rather than the competencies individual professionals need to exercise once assimilation has occurred.

Gartner's HR practice survey data illustrate the resulting practice gap. CHROs surveyed by Gartner report that only 8% of HR leaders believe their managers can use AI effectively (Gartner, 2025a). Separately, only 7% of organisations provide guidelines on how employees should use time saved by AI (Gartner, 2025b); while this statistic concerns time-redeployment guidance rather than output-interpretation guidance specifically, the absence of structured guidance in even this narrower domain suggests that interpretive guidance is unlikely to be more prevalent. Only 14% of managers surveyed report receiving support for integrating generative AI into daily tasks (Gartner, 2025b). Gartner (2026a) describes this as an "enablement illusion", the mistaken equation of access and adoption metrics with genuine capability. The problem this evidence exposes is conceptual as much as practical. Data literacy, as conventionally defined, treats algorithmic outputs as transparent data points to be read correctly. It equips a professional to read a score, not to judge what the score omits, weigh it against contextual knowledge the algorithm lacks, communicate it in a way that preserves an employee's sense of fairness, or recognise when it should be overridden. Sandberg (2000) offers a useful distinction from the broader competence literature: competence is not a

fixed inventory of attributes but the meaning that work takes on for the person performing it, understood through situated interpretation rather than checklist mastery. Applied here, the gap between reading an AI-generated score and knowing what to do with it is an interpretive gap, not an information gap, and it is this gap that the construct developed in this paper is designed to close.

The epistemic layer of the framework draws on algorithmic literacy scholarship that specifies more precisely what “reading” an algorithm involves. [Cetindamar et al. \(2024\)](#) map AI literacy across technical, cognitive and ethical dimensions for digital-workplace employees generally. [Yuan et al. \(2024\)](#) operationalise a six-dimensional literacy scale spanning AI features, processing, algorithmic influence, user efficacy, ethical consideration and threat appraisal, structured across individual, interactive and sociocultural levels; their interactive and sociocultural dimensions partially overlap with this paper’s core interpretive and relational competencies, but their scale measures general AI literacy independent of professional role and institutional context, the two factors this framework treats as constitutive. [Annapureddy et al. \(2025\)](#) extend this line of work to generative AI specifically, defining twelve constituent competencies. Each of these contributions treats literacy as a property an individual either has or lacks, largely independent of the organisational role that individual occupies. None asks what changes when the object of literacy is not a general-purpose AI tool but an algorithmic system that produces a judgement about another person’s livelihood, and none asks how employees on the receiving end of that judgement respond. [Tandon et al. \(2025\)](#) begin to close this second gap, documenting a duality of employee perceptions toward algorithmic HRM that mixes uncertainty, aversion and appreciation depending on how the system is implemented and communicated, a finding that reinforces this paper’s contention that the manner of algorithmic mediation, not only its accuracy, is itself a competency object. [Kellogg et al. \(2020\)](#) supply the organisational-control vocabulary this paper draws on for the “contest” component of algorithmic interpretive competence: their synthesis of algorithmic control mechanisms describes workplaces as a contested terrain in which workers, and by extension the HR professionals who mediate on their behalf, retain some capacity to resist, renegotiate or override algorithmic direction rather than simply comply with it. Algorithmic interpretive competence, as defined in this paper, is the capacity that determines whether that contestation capacity is exercised competently or not at all.

AIC is not, however, the only construct that addresses the space between AI systems and the professionals who work with them. AI literacy ([Cetindamar et al., 2024](#)), algorithmic literacy ([Yuan et al., 2024](#)), ethical competence, cultural intelligence, professional judgement, and human-AI collaboration competence ([Chowdhury et al., 2023](#)) each capture part of this territory. Section 4.5 below specifies what AIC shares with, excludes from, and adds beyond each of these adjacent constructs, and Section 4.6 states the construct’s measurement architecture. These boundary and measurement specifications respond directly to the need, identified

across the AI-HRM literature, for constructs that are precise enough to be empirically discriminated from their neighbours.

2.3. Institutional Theory and Institutional Voids in Sub-Saharan Africa

North's (1990) foundational account of institutions as the humanly devised constraints that structure economic and organisational behaviour underlies the institutional layer of this framework: institutions, formal and informal, reduce uncertainty by establishing stable expectations about how transactions, including the transaction between an algorithm's output and an employee's livelihood, will be governed. Scott's (2014) institutional theory specifies the mechanisms through which this happens and explains why identical AI-augmented PM technology can generate different competency demands across settings. The regulative pillar concerns the laws and enforcement mechanisms that govern data use and algorithmic accountability; the normative pillar concerns the professional standards and codes that shape what "good" HR practice means; and the cognitive pillar concerns the taken-for-granted assumptions about work and fairness that employees and managers bring to an algorithmic system. Where all three pillars are well developed, as in jurisdictions operating under the European Union's AI Act, the focal HR professional can rely on external scaffolding: a regulator to consult, a professional body to set standards, and a cultural expectation of algorithmic accountability that is already partly established. Khanna and Palepu's (2010) institutional voids framework describes what happens when this scaffolding is absent: the specialised intermediaries that developed markets take for granted, regulatory bodies, data governance frameworks, AI ethics boards, digital skills ecosystems, do not exist or are nascent, and organisational actors must internalise the functions those intermediaries would otherwise perform.

Sub-Saharan Africa is not institutionally homogeneous, and three tiers of institutional development are relevant to this framework's argument. South Africa and Kenya represent the relatively advanced tier: South Africa's Protection of Personal Information Act (POPIA, 2013, fully enforced from 2021) establishes data-subject rights and processing conditions comparable in structure to the EU's GDPR, while Kenya's Data Protection Act (2019) similarly creates enforceable protections. Both countries have operational data protection authorities. Nigeria and Ghana represent an intermediate tier: Nigeria's Data Protection Act (2023) and Ghana's Data Protection Act (2012) are enacted but enforcement capacity and public awareness remain uneven. The majority of SSA countries occupy a third tier in which data protection and AI governance legislation is either absent, unenforced, or in early draft stage. Internet penetration across the region stood at 38% in 2024 against a global average of 68%, and the urban-rural divide, 57% against 23%, is the largest of any region tracked by the International Telecommunication Union (2025). Mobile broadband covers 86% of the population, yet fifth-generation coverage reaches only 11%, concentrated in urban hubs, and entry-level mobile broadband

costs 3.9% of average income against a policy target of 2% ([International Telecommunication Union, 2025](#)). On the regulatory pillar, only 18% of African countries have reached the most advanced tier of ICT regulatory maturity, compared with 38% globally ([International Telecommunication Union, 2025](#)). The ITU's ICT regulatory maturity measure captures general telecommunications and digital-market governance, not AI-specific or PM-specific regulation; it is used here as a proxy indicator of broader institutional capacity, not as a direct measure of algorithmic-PM governance readiness. [Owor et al. \(2025\)](#), in a regional systematic review of AI-driven HRM practices across SSA, conclude that HR professionals across the continent frequently lack training in algorithmic reasoning, data analytics or AI ethics, and that existing digital-skills initiatives target IT professionals rather than HR practitioners, leaving a function-specific training void.

Institutional voids of this kind are not unique to HRM. [Moharrak et al. \(2024\)](#) apply the technology-organisation-environment framework to AI adoption in Africa's transportation sector and reach a structurally identical conclusion: institutional voids function simultaneously as constraints and as latitude for locally adapted innovation. [AfriCatalyst \(2025\)](#), an independent development advisory firm, reports that Africa's digital economy is forecast to grow from 5.2% of GDP in 2025 to 8.5% by 2050, and that current AI applications on the continent concentrate in data analytics, e-learning and chatbots rather than performance management, indicating substantial unclaimed ground. [McKinsey's \(McKinsey & Company, 2025a\)](#) analysis of Africa's generative AI opportunity reaches a complementary conclusion: realising AI's value on the continent requires genuine business transformation, not merely technology deployment. This gap is not unique to SSA: [McKinsey's \(McKinsey & Company, 2025b\)](#) global survey finds that although 88% of organisations now use AI in at least one business function, up from 78% the previous year, nearly two-thirds have not yet begun scaling it across the enterprise, and only around 6% qualify as high performers capturing significant EBIT value from it, suggesting that the institutional voids characterised above amplify a capability gap that exists globally rather than creating it from nothing. Institutional isomorphism, [DiMaggio and Powell's \(1983\)](#) demonstration that organisations facing uncertainty often adopt practices that confer legitimacy through mimetic imitation independently of whether local conditions support effective implementation, supplies one explanation for why organisations might adopt AI-augmented PM systems ahead of the institutional and competency scaffolding needed to govern them well. [Coetzee et al. \(2025\)](#), in a South African study, find that future-proof HR competencies function as synergetic boosters of workplace stewardship capability specifically when developed as an integrated bundle rather than acquired piecemeal.

The Ubuntu-informed relational logic advanced in this paper is a normative theoretical resource, not an empirical claim that all SSA workplaces operate according to communal principles. Whether and how Ubuntu values manifest in specific organisational performance-management practices is an empirical ques-

tion this framework invites rather than presupposes. Ubuntu philosophy, the relational conception of personhood captured in the maxim that a person is a person through other persons (Mangaliso, 2001; Mbiti, 1990), implies that performance evaluation is legitimate to the extent that it is experienced as participatory and communally embedded, not simply as accurate in a narrow metric sense. A competency framework built only around infrastructural deficit would miss this cultural dimension entirely; the framework developed in Section 4 treats it as a distinct normative resource for the relational-cultural component of AIC rather than a gap to be closed by imported models.

2.4. Competence Theory and the HR Competency Paradigm

The competence theory literature offers the conceptual resources to specify what “having” the right knowledge should mean for interpretive work of this kind. McClelland’s (1973) foundational argument, that competence, not intelligence or credential, predicts occupational success, launched a modelling tradition later extended by Boyatzis (1982) and by Spencer and Spencer (1993), whose iceberg model distinguishes visible competencies, knowledge and skill, from the largely hidden motives, traits and self-concept that determine how that knowledge is actually deployed in practice. Le Boterf’s (2011) competence-in-action framework sharpens the distinction further and is the anchor for the argument developed here: competence is not a static attribute a person possesses but a contextualised mobilisation of resources, knowledge, skill and disposition, in situated action. Le Boterf (2011) is the sole non-English-language source in this review; it is included because the competence-in-action (competence en acte) framework it introduces has no English-language equivalent of comparable theoretical depth, and the concept is central to the paper’s construct architecture. Sandberg’s (2000) interpretive approach reinforces the same point empirically: workers’ competence is constituted by the meaning their work takes on for them, not by an inventory of attributes checked off in the abstract. Applied to AI-augmented PM, the distinction is decisive. Data literacy describes what a professional has; it says nothing about what that professional does when an algorithmic score conflicts with contextual knowledge, or when an employee challenges an AI-generated rating. Competence-in-action, by contrast, is precisely the capacity this paper seeks to specify.

Ulrich and Dulebohn (2015) provide the established HR competency baseline against which this paper’s framework is positioned. Their six-role model, Strategic Positioner, Credible Activist, Capability Builder, Change Champion, HR Innovator and Integrator, and Technology Proponent, remains widely cited, but the Technology Proponent role predates the generative AI era and is defined generically: it specifies that HR professionals should leverage technology to improve performance but says nothing about how a professional should interpret, translate, mediate or contest what an algorithm produces. This paper’s argument is that the Technology Proponent role, adequate for describing technology adoption in general, must be unbundled into distinct, PM-specific capacities once AI moves from

an administrative tool to a co-producer of performance judgements.

3. Methodology: Integrative Literature Review

This paper adopts an integrative literature review design (Torraco, 2005, 2016) combined with conceptual framework development. The design is appropriate here because the task is synthetic rather than confirmatory: no single empirical study addresses the intersection of AI-augmented performance management, HR professional competence, and institutional context in Sub-Saharan Africa, and the contribution required is a coherent theoretical framework built from previously disconnected literatures. The paper adopts a pragmatist epistemological position, treating the integration of normative competence specification, what HR professionals ought to be able to do, with descriptive institutional analysis, how context shapes what they can realistically do, as complementary rather than contradictory tasks. The review was conducted by a single author; no second reviewer or inter-coder reliability check was applied. This is acknowledged as a limitation (Section 6.3).

3.1. Search Architecture: Two Streams

The literature search followed a dual-stream architecture designed to accommodate two distinct source categories with different inclusion logics.

Stream A (Systematic search, 2015 - 2026). Database-driven searches were conducted in Scopus and Web of Science using the following reconstructed Boolean search strings, applied to title, abstract and keyword fields:

- (“artificial intelligence” OR “algorithmic management” OR “AI-augmented” OR “machine learning”) AND (“performance management” OR “performance appraisal” OR “performance evaluation” OR “performance review”)
- (“artificial intelligence” OR “algorithmic management”) AND (“HR competenc*” OR “human resource competenc*” OR “data literacy” OR “AI literacy” OR “algorithmic literacy”)
- (“artificial intelligence” OR “algorithmic management”) AND (“Sub-Saharan Africa” OR “SSA” OR “Africa” OR “developing countr*” OR “emerging market*”) AND (“human resource*” OR “HRM”)

The search window was January 2015 to June 2026. Inclusion criteria for Stream A were: English-language peer-reviewed journal articles, scholarly books published by academic presses, and institutional or industry reports from recognised organisations (Deloitte, World Economic Forum, McKinsey, Gartner, SHRM, CIPD, ITU). Non-peer-reviewed opinion content, magazine articles and duplicate records were excluded. This database search was supplemented by backward and forward citation tracking from three anchor papers: Deepa et al. (2024), Priksat et al. (2023) and Poisat et al. (2024), selected because each addresses one leg of the paper’s theoretical architecture: general AI-HR competency, AI-HRM assimilation, and SSA-specific empirical evidence, respectively. Industry and press-release material from Gartner, Deloitte, the World Economic Forum and McKinsey was retained deliberately because the phenomenon under study, organisational AI

adoption in performance management during 2025 and 2026, is too recent for the peer-review cycle to have produced comparable large-sample survey evidence; each such source is used for descriptive statistics rather than for causal claims, and its vendor or consultancy status is identified explicitly in-text (see Section 2.2's treatment of Worklytics and the differentiated Gartner citation entries).

Stream B (Foundational theoretical works, pre-2015). A separate, explicitly named set of twelve pre-2015 sources was included because they are canonical works in the theoretical traditions the framework draws on: institutional theory (North, 1990; DiMaggio & Powell, 1983; Scott, 2014), competence theory (McClelland, 1973; Boyatzis, 1982; Spencer & Spencer, 1993; Le Boterf, 2011; Sandberg, 2000), Ubuntu philosophy (Mbiti, 1990; Mangaliso, 2001), institutional voids (Khanna & Palepu, 2010), and review methodology (Torraco, 2005). The inclusion rule is stated explicitly: foundational works that supply the theoretical vocabulary the framework requires, identified through the author's prior disciplinary knowledge rather than through database search.

A complete PRISMA-style screening record was not maintained during the original search process and cannot be reconstructed retrospectively; this is acknowledged as a limitation of the review's reproducibility (Section 6.3). The reconstructed Boolean strings and search dates above are post-hoc documentation of the search logic and should be treated as approximations rather than exact reproductions of the original queries.

3.2. Corpus Composition and Quality Appraisal

Of the 53 sources retained in the final synthesis, 41 entered through Stream A (the systematic search and citation tracking within the 2015 - 2026 window) and 12 through Stream B (foundational theoretical works predating 2015). By source type, the corpus comprises 29 peer-reviewed journal articles, 7 scholarly books, 16 industry or institutional reports (including press releases), and 1 preprint not yet peer-reviewed (Konjen, 2025). Since this is an integrative review following Torraco's (2005, 2016) methodology rather than a systematic review requiring formal quality appraisal (e.g., CASP), source quality was assessed through source-type classification and cross-checking of industry data against independent sources reporting directionally consistent findings, a practice described by Torraco (2016) as appropriate for reviews that synthesise across heterogeneous source types.

3.3. Analytical Procedure

Three broad categories, institutional, competence and epistemic, structured the coding of sources during synthesis (a coding-stage simplification distinct from the five specific theoretical traditions the resulting framework draws upon and justifies individually in Section 6.1): each source was coded against which category it primarily informed, which of the four competency dimensions developed in Section 4 it evidenced, and whether it supplied SSA-specific data. This coding served two purposes: it ensured that every theoretical claim in the resulting framework could be traced to

a specific evidentiary source, and it surfaced the boundary between generalisable AI-HRM findings and findings specific to institutionally constrained settings, a distinction the framework depends on directly. Where the review draws on secondary empirical studies from South Africa (Poisat et al., 2024; Coetzee et al., 2025) and a regional systematic review (Owor et al., 2025), it does so as illustrative anchoring for the theoretical claims rather than as a pooled empirical test, consistent with established practice in conceptual HRM scholarship that draws on published empirical findings to ground, rather than statistically verify, a proposed framework. **Table A1** (Appendix) provides the complete source-by-code evidence matrix, mapping each of the 53 sources against its coding category, competency dimension(s), SSA-specific status, and source type. For example, Poisat et al. (2024) was coded as: Competence category (it primarily informs what competence looks like in practice rather than institutional or epistemic content); Dimension D2-RC (it evidences the relational-cultural component of AIC, specifically employee-trust and engagement concerns); SSA-specific: Yes (it reports South African survey data); Source type: Peer-reviewed. This same four-field procedure, coding category, competency dimension, SSA-specific status, source type, was applied to each of the 54 entries in **Table A1**, giving a fully auditable classification even though the identification-and-screening counts from the original search itself could not be reconstructed (Section 6.3).

Two further procedural choices merit explanation. The treatment of industry and press-release material, which supplies a substantial share of the quantitative evidence cited in Sections 2 and 4, follows a deliberate protocol: each Gartner statistic is matched to the specific Gartner publication that contains it (see the differentiated Gartner reference entries), each such source is used for descriptive statistics rather than causal claims, and its commercial or consultancy status is identified in-text. The boundary between generalisable algorithmic-management literature, which spans gig-economy and platform-work contexts (Duggan et al., 2020; Keegan & Meijerink, 2025; Meijerink & Bondarouk, 2023), and literature specific to performance management is maintained consistently: gig-economy findings are used to establish general mechanisms of algorithmic control and contestation that plausibly transfer to conventional PM settings, not as direct evidence about PM itself.

4. A Contextualised Competency Framework for AI-Augmented Performance Management

4.1. Construct Architecture: Antecedents, Core AIC, and Enabling Conditions

This section restructures the framework around a three-tier construct architecture that distinguishes antecedents, core AIC, and enabling conditions. This restructuring responds to the observation that AIC, as originally conceived, combined tool operation, model understanding, contextual judgement, communication, culture, ethics, law, privacy, fairness auditing, impact assessment, advocacy, and override authority, an overextension that made the construct difficult to differentiate empirically from adjacent constructs such as AI literacy, ethical competence, or cultural intelligence.

Antecedents (must be present for AIC to operate, but are not AIC itself): technical-algorithmic literacy, the capacity to operate, configure and understand the basic functioning of AI-based PM tools (the tool-operation and model-understanding components of what was previously labelled Dimension 1), and basic ethical-regulatory knowledge, including data protection awareness, bias recognition and the elements of algorithmic accountability that can be codified in training or policy.

Core AIC (the construct proper): contextual interpretation, translation, professional judgement about override, and culturally situated communication of algorithmic outputs. This is the interpretive-hermeneutic and relational-cultural work that existing frameworks do not name: the capacity to establish what an algorithmic score means in context, to identify what it structurally cannot capture, to bridge quantitative outputs with qualitative knowledge of an employee's actual contribution, and to convert that synthesis into feedback the employee will experience as meaningful rather than mechanical. AIC is defined as the contextual interpretation and professional judgement applied to algorithmic PM outputs by the focal HR professional.

Enabling conditions (organisational and institutional, not individual level): decision authority allocation (Kim et al., 2024), governance structures, and regulatory scaffolding. These determine whether the focal HR professional has the organisational permission and infrastructure to exercise AIC, but they are properties of the organisation and its institutional environment, not of the individual professional.

A related clarification concerns where responsibility for governance tasks actually sits. Bias review, privacy protection, legal compliance and algorithmic impact assessment are not the sole responsibility of the focal HR professional, and this framework does not portray individual competence as a substitute for organisational governance structures. These tasks require distributed responsibility across HR, line managers, technical or data specialists, legal advisers, technology vendors and, where they exist, worker representatives. The focal HR professional's ethical-regulatory knowledge (an antecedent introduced above) functions as one node within this distributed system, primarily the node responsible for recognising when a PM-specific ethical or legal issue requires escalation to one of these other actors, rather than as the system's sole locus of accountability.

The four components introduced above are distinguished from one another along a single consistent axis: the type of judgement each requires. Technical-algorithmic literacy (antecedent) requires an accuracy judgement, is the algorithmic output technically sound, correctly computed from the data it was given. Ethical-regulatory knowledge (antecedent) requires a compliance judgement, does the output, and its use, meet applicable legal and normative thresholds. Contextual-interpretive competence (core) requires a meaning judgement, what does this output signify for this employee, in this organisational and cultural context. Relational-cultural competence (core) requires a relational judgement, how should this output be communicated so as to preserve trust and dignity in the relationship between the employee and the organisation. This single axis, the object of judgement moving from the algorithm's output itself (accuracy, compliance) to what

that output means and how it should be conveyed to a person (meaning, relational), is what separates the four components analytically even though all four routinely operate together on the same algorithmic output in practice.

AIC does not encompass general AI literacy (the broad capacity to understand AI systems independent of professional role), nor does it extend to organisational-level AI governance architecture (the allocation of decision rights, vendor oversight, and regulatory compliance structures). These are antecedents and enabling conditions, respectively, that AIC requires but does not itself constitute.

What survives as AIC's distinctive core, after every overlap catalogued in **Table 1** is granted, is not any single capability that adjacent constructs lack entirely, but a specific combination that no adjacent construct assembles in the same way: professional judgement (shared in part with HR professional judgement generally) applied specifically to algorithmic outputs (shared in part with AI and algorithmic literacy) in a manner that is accountable to a named employee's justice perceptions (shared in part with ethical competence) and calibrated to a specific organisational and cultural setting (shared in part with cultural intelligence). AI literacy and algorithmic literacy describe a person's understanding of AI systems in general; they do not specify what that understanding is for once an algorithm has produced a judgement about a particular employee's pay or promotion. Ethical competence and cultural intelligence describe general dispositions; they are not anchored to the specific interpretive task of reconciling an algorithmic score with what an HR professional independently knows about the employee it describes. AIC-core is this reconciliation task itself, treated as professional competency with its own accuracy, compliance, meaning and relational demands, rather than as an application of general capabilities that happen to be relevant to AI-augmented PM.

The demand-side evidence for the antecedent layer is unambiguous. **Deepa et al. (2024)** find, in a peer-reviewed systematic review of HR managers' AI-adoption competencies, that technical and social competency gaps are a primary barrier to effective AI use in HR functions generally, a pattern the more recent industry data corroborate at larger scale: SHRM records HR technology skills growing at 23% annually against a 1% decline in non-technology HR skills over the same period (**Society for Human Resource Management, 2025**), the World Economic Forum finds 90% of employers expecting AI and big-data skill demand to rise (**World Economic Forum, 2025**), and SHRM's 2026 survey finds AI currently adopted in only 39% of HR functions, with a further 7% planning adoption within the year (**Society for Human Resource Management, 2026**), indicating a function still in the early stages of technical capability-building. This antecedent layer is, however, necessary but insufficient in the following specific sense: 95% of CHROs surveyed by Gartner had adopted AI by the end of 2025 while nearly three-quarters of HR leaders report only moderate or minimal returns from their AI investments (**Gartner, 2026b**), a pattern inconsistent with technical adoption alone driving governance effectiveness.

4.2. Core AIC Dimension 1: Contextual-Interpretive Competence

Contextual-interpretive competence is the capacity to translate an algorithmic

score into its organisational and cultural context, to identify what a given metric structurally cannot capture, to bridge quantitative outputs with qualitative knowledge of an employee's actual contribution, and to convert that synthesis into feedback the employee will experience as meaningful. Gartner's (2026b) proficiency data illustrate the returns to this capacity concretely: employees who are proficient with AI across multiple use cases are twice as likely to be highly productive and 2.3 times more likely to produce high-quality work than those who are not, a multiplier that reflects interpretive skill rather than mere tool access. Tong et al. (2021) provide the clearest theoretical demonstration of why this dimension cannot be reduced to data literacy: their field experiment shows that AI-generated feedback and human-communicated feedback produce systematically different employee responses, a "deployment effect" and a "disclosure effect", even holding feedback content constant, which means that how an output is communicated is itself a competency, not a downstream implementation detail. Liu et al. (2024) show a related mechanism from the employee side: algorithmic management inhibits improvisational and creative performance, particularly where employees perceive themselves as dependent on the algorithm rather than in dialogue with it. Konjen (2025) documents that algorithmic systems structurally overlook intangible contributions such as collaborative problem-solving and empathetic support.

In much of SSA these blind spots are amplified rather than incidental. Communal problem-solving, informal mentoring and the overlap between formal and informal economic activity are pervasive features of work in the region that leave little digital trace and are consequently invisible to algorithmic PM systems calibrated on data-rich, formally structured Global North workplaces (Owor et al., 2025). Multilingual work environments compound the interpretive burden further, since sentiment and communication-pattern analytics trained predominantly on English-language corpora may misread performance signals expressed in French, Portuguese or indigenous languages.

The broader algorithmic-management literature offers a further reason this dimension cannot be delegated to the algorithm's designers. Duggan et al. (2020) show, in the gig-economy setting where algorithmic management first became pervasive, that algorithmic control operates simultaneously as a constraint on worker autonomy and, when designed and mediated well, as a source of flexibility and value; Meijerink and Bondarouk (2023) formalise this as the duality of algorithmic management, arguing that the same algorithmic input can limit or expand employee autonomy depending on how it is embedded in organisational practice. Keegan and Meijerink (2025) trace how algorithmic management has moved from an edge case confined to platform work to a mainstream feature of conventional HRM. The practical implication is that contextual-interpretive competence determines which side of the duality an organisation experiences: the same AI-augmented PM system can constrain or empower employees depending on whether the focal HR professional possesses the interpretive skill to tip the balance toward value creation.

4.3. Core AIC Dimension 2: Relational-Cultural Competence

Relational-cultural competence is the ability to sustain trust, engagement and dignity in performance relationships that are increasingly mediated by algorithms. It encompasses Ubuntu-informed communal assessment practices (understood as a normative resource, not a universal empirical descriptor), participatory design of PM processes, active trust-building under conditions of algorithmic monitoring, and culturally sensitive delivery of feedback. This dimension performs distinct compensatory work under the institutional conditions described in Section 2.3: where technical infrastructure is constrained and regulatory scaffolding is thin, relational-cultural competence can partially sustain employee trust and engagement while those constraints are being addressed through other means. This partial compensation operates on the trust and engagement pathway, not on the decision-validity pathway: relational competence cannot correct technically invalid algorithmic outputs, only sustain employee engagement while those outputs are being improved. Gartner's (2026b) evidence that employees with a positive outlook towards AI are 3.4 times more likely to be highly productive is consistent with this framing, and with Gartner's (2025c) finding that 65% of employees report being excited to use AI at work, a baseline receptivity that relational-cultural competence is positioned to convert into sustained engagement. Deloitte's (2025) finding that approximately 70% of workers welcome AI-driven personalisation, provided it is implemented in ways that respect their agency, points in the same direction. Poisat et al. (2024), in a small exploratory study of South African HR managers' perceptions of AI's workforce impact, find that respondents perceive the impact clearly but report limited hands-on AI adoption experience, a gap consistent with, though not a direct measure of, the relational-competence deficit this dimension theorises.

4.4. Antecedent: Technical-Algorithmic Literacy

Technical-algorithmic literacy is the ability to operate, configure and understand the basic functioning of AI-based PM tools: entering data correctly, understanding how a given metric is constructed, interpreting output formats, adjusting tool configuration, and reasoning in elementary terms about how an algorithm arrives at a score. It is the most closely aligned antecedent with conventional data literacy. In much of SSA this antecedent carries distinctive constraints: enterprise-grade PM platforms typically assume stable broadband and desktop access that much of the regional workforce does not have; mobile-first platforms are consequently the realistic entry point, but they narrow the functionality that can practically be delivered (International Telecommunication Union, 2025).

4.5. Construct Boundary: What AIC Shares with, Excludes from, and Adds beyond Adjacent Constructs

AIC occupies conceptual territory that overlaps with several established constructs, but it is not reducible to any one of them. AI literacy (Cetindamar et al., 2024), algorithmic literacy (Yuan et al., 2024) and generative AI competencies

(Annapureddy et al., 2025) provide the technical and cognitive foundations required to understand how AI systems function and how algorithmic outputs are generated. However, these constructs are generally role-independent and do not specify what a human resource professional should do when an algorithmic output becomes the basis for a consequential performance-management judgement. In the present framework, such literacy therefore functions primarily as an antecedent to AIC rather than as part of its distinctive core.

A similar boundary applies to ethical competence, cultural intelligence, professional judgement (Ulrich & Dulebohn, 2015) and human-AI collaboration (Chowdhury et al., 2023). Ethical competence contributes the capacity to recognise bias, fairness concerns and accountability issues, while cultural intelligence contributes sensitivity to cross-cultural differences. Professional judgement provides the broader capacity for contextual decision-making, and human-AI collaboration captures the ability to work effectively with intelligent systems. Yet none of these constructs, taken independently, is anchored to the specific task that defines AIC: interpreting an algorithmic performance output about a particular employee, situating that output within organisational and cultural context, deciding whether and how it should influence a high-stakes HR decision, and communicating that judgement in a way that preserves procedural and interactional justice.

As argued in Section 4.1, the distinctive contribution of AIC lies not in claiming entirely novel component capabilities, but in assembling them around a specific professional object of judgement: the reconciliation of algorithmic output with contextual knowledge of the employee and the organisation. AIC is also distinguished from organisational-level human-AI capability frameworks, because it is theorised at the level of the individual HR professional responsible for governing AI-augmented performance management. Table 1 summarises these construct boundaries by showing what AIC shares with adjacent constructs, what it excludes, and what it adds in the specific context of AI-augmented performance management.

Table 1. Construct boundary analysis: AIC against adjacent constructs.

Adjacent Construct	What AIC Shares	What AIC Excludes	What AIC Adds
AI literacy (Cetindamar et al., 2024)	Technical and cognitive AI knowledge	General-purpose AI understanding independent of role	PM-specific interpretive judgement; institutional contextualisation
Algorithmic literacy (Yuan et al., 2024)	Features, processing, efficacy	Interactive/sociocultural dimensions measured independently of role	Professional override judgement; culturally situated PM communication
GenAI competencies (Annapureddy et al., 2025)	Awareness to critical evaluation	Role-independent citizen capacities	Org-role-specific, PM-stage-specific application
Ethical competence	Bias recognition, fairness	Ethics as self-standing domain	Ethics applied to algorithmic PM override
Cultural intelligence	Cross-cultural adaptation	General intercultural skill	Ubuntu-informed communal assessment norms specific to SSA PM contexts
HR professional judgement (Ulrich & Dulebohn, 2015)	Contextual decision-making	Pre-AI judgement paradigm	Judgement applied to AI-generated PM outputs
Human-AI collaboration (Chowdhury et al., 2023)	Capacity to work with AI	Organisational-level construct	Individual-level interpretive capacity

4.6. Mapping AIC onto the Performance Management Cycle

The following table maps the core AIC dimensions and their antecedent onto the stages of a canonical PM cycle (**Table 2**), specifying the distinctive interpretive demand at each stage. This mapping directly addresses the question of what PM-specific work AIC does that generic competency frameworks do not specify.

Table 2. Mapping AIC dimensions onto the performance management cycle.

PM Cycle Stage	Primary AIC Dimension(s)	Antecedent Required	Distinctive Interpretive Demand
Goal setting and metric selection	Contextual-interpretive	Technical-algorithmic literacy	Judging which metrics the algorithm can and cannot capture
Continuous monitoring	Contextual-interpretive + ethical knowledge	Technical-algorithmic literacy	Detecting surveillance overreach; privacy boundaries
Appraisal and rating calibration	Contextual-interpretive + relational-cultural	Technical-algorithmic literacy	Contextualising scores; recovering intangible contributions
Feedback delivery	Contextual-interpretive + relational-cultural	Technical-algorithmic literacy	Communicating algorithmic assessments with dignity
Pay and promotion decisions	Contextual-interpretive + ethical knowledge	Technical-algorithmic literacy	Override judgement; bias detection in high-stakes outcomes
Discipline and corrective action	Contextual-interpretive + ethical knowledge	Technical-algorithmic literacy	Judging whether an algorithmic flag warrants formal escalation vs. contextual explanation
Employee voice and appeal	Relational-cultural + ethical knowledge	Technical-algorithmic literacy	Facilitating meaningful challenge to algorithmic decisions

4.7. Measurement Architecture

The construct architecture described above is theorised as a **formative, conjunctive system with partial compensability**: each component contributes distinctly to the higher-order construct (formative), both core dimensions and the antecedent are in principle necessary for fully effective PM governance (conjunctive), but under conditions of institutional constraint, relational-cultural competence can partially compensate for limitations in technical-algorithmic literacy in sustaining employee trust and engagement, a claim made explicitly in Proposition 3 and bounded by the institutional-voids conditions specified in Proposition 2. This partial compensability does not imply full substitutability: relational competence cannot correct technically invalid algorithmic outputs, only sustain trust and engagement while those outputs are being improved through other means. Empirical validation should test this architecture through formative measurement models (e.g., PLS-SEM) rather than reflective factor analysis, since the dimensions are theorised as causally distinct contributors to a composite rather than interchangeable indicators of an underlying latent variable.

4.8. The Verb-to-Dimension Mapping

The four verbs in the AIC definition (interpret, translate, mediate, contest) are not evenly distributed across the construct architecture. **Technical decoding**, establishing what the algorithm in fact produced, is primarily the work of the antecedent

(technical-algorithmic literacy). Translation is the core work of contextual-interpretive competence: converting that output into organisational and cultural meaning. Contestation draws principally on the ethical-regulatory knowledge antecedent and the enabling-condition layer: the judgement of when an algorithmic recommendation should be overridden rather than merely accepted, and the organisational permission to do so. Mediation is the one verb that is not the province of a single component: communicating an interpreted, contextualised output to an employee in a way that sustains trust and dignity draws jointly on contextual-interpretive and relational-cultural competence. This distribution is why the construct components do not map one-to-one onto the four verbs, and why all components remain necessary rather than redundant with one another. **Figure 1** summarises the full construct architecture developed across this section, showing how the antecedents, the core dimensions and the enabling conditions relate to one another.

Construct Architecture of Algorithmic Interpretive Competence (AIC)

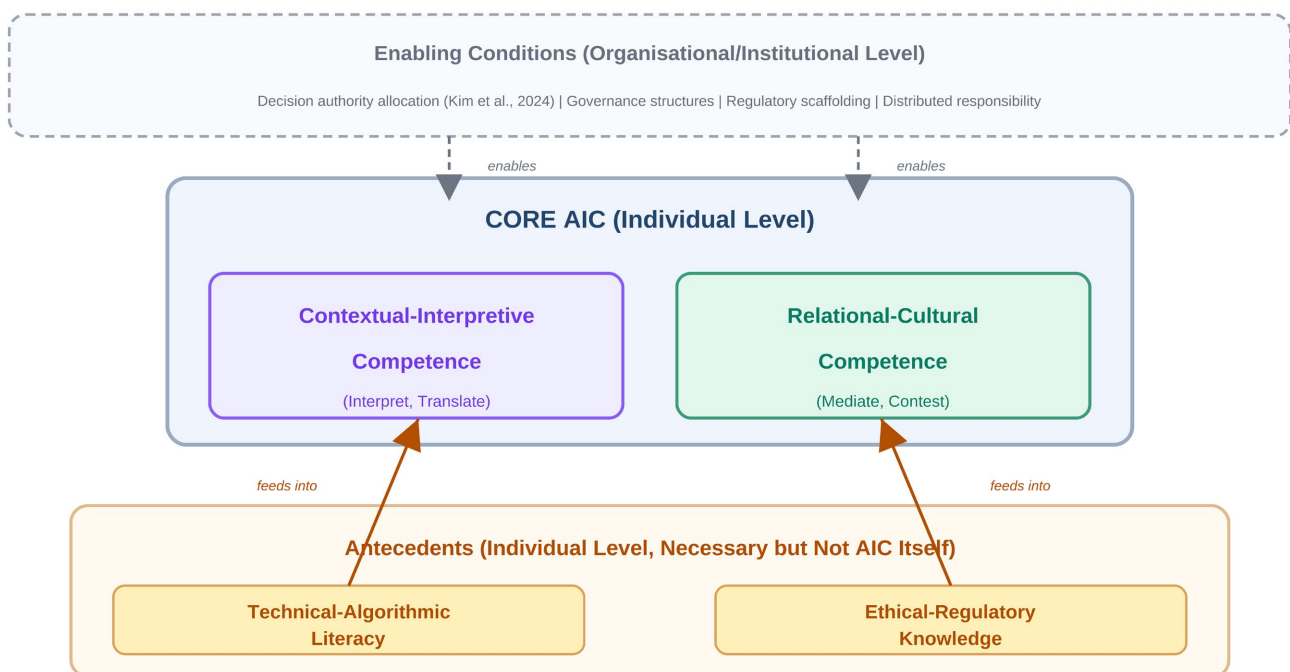


Figure 1. Construct architecture of algorithmic interpretive competence (AIC).

The three-tier construct architecture shows enabling conditions (organisational/institutional level) at the top, core AIC (individual level: contextual-interpretive and relational-cultural competence) in the centre, and antecedents (individual level: technical-algorithmic literacy and ethical-regulatory knowledge) at the bottom.

5. Propositions and Boundary Conditions

The framework developed in Section 4 yields five propositions. Each specifies the level of analysis for its key variables, names at least one rival mechanism, and includes a falsifiability clause. The industry data cited alongside each proposition

illustrates rather than establishes it: the propositions are theoretically derived from the framework, and the falsifiability clauses are what a future empirical test is designed to adjudicate. The focal actor across all propositions is the HR professional responsible for governing the AI-augmented PM system (individual level). Institutional voids are measured at country or sector level. PM governance effectiveness and its constituent outcomes (procedural justice, interactional justice, trust, engagement) are measured at organisational level (governance effectiveness) and employee level (justice perceptions, trust, engagement). AIC is theorised as a pre-existing or co-developing capacity, not as a consequence of AI-augmented PM adoption. All five propositions assume an organisational context in which some form of AI-augmented PM system has already been adopted.

Proposition 1. In organisations that have adopted AI-augmented PM systems, the focal HR professional's technical-algorithmic literacy (antecedent, individual level) predicts PM governance effectiveness (organisational level) only when accompanied by contextual-interpretive competence (core AIC, individual level); technical-algorithmic literacy alone does not significantly predict governance effectiveness.

Rival mechanism: An alternative explanation is that technical-algorithmic literacy is sufficient but its effect is suppressed by poor organisational change management; P1 would be falsified if technical-algorithmic literacy alone, without contextual-interpretive competence, significantly predicted governance effectiveness across a representative sample of organisations after controlling for change-management quality.

Proposition 2a. Weak national AI regulatory frameworks (country level, measured as ITU G4 regulatory maturity below Tier 4) strengthen the positive relationship between the focal HR professional's contextual-interpretive competence (individual level) and employees' procedural-justice perceptions (employee level).

Proposition 2b. Limited organisational AI skills infrastructure, meaning the availability of AI-specific training and competency-development programmes for HR staff (organisation level), strengthens the same relationship.

Proposition 2c. Limited technical and connectivity infrastructure, meaning broadband access, tool availability and platform reliability (country or organisation level, as characterised in Section 2.3), strengthens the same relationship independently of P2a and P2b. Regulatory maturity, skills availability and technical infrastructure are treated as three distinct institutional-void dimensions rather than a single undifferentiated construct, since an organisation can be well regulated but poorly connected, or well-connected but without trained staff, and each configuration carries different implications for where an intervention would have to target.

Specification: P2a, P2b and P2c are cross-level moderation effects testable via multilevel modelling (HLM or multilevel SEM), with individual-level AIC nested within organisations nested within countries. The three dimensions are not assumed to covary perfectly and should be measured as separate indicators in any empirical test.

Rival mechanism: The moderation effect could be driven by selection (organi-

sations in weaker institutional environments that adopt AI-PM are systematically different from those that do not) rather than by the institutional-voids mechanism itself. P2a, P2b and P2c would each be falsified if their respective interaction terms (regulatory maturity x AIC; skills infrastructure x AIC; technical infrastructure x AIC) did not significantly predict procedural-justice perceptions, or if the moderation effects were fully accounted for by organisational selection controls.

Proposition 3. Under conditions of constrained technical infrastructure (as characterised in Section 2.3), the focal HR professional's relational-cultural competence (core AIC, individual level) partially compensates for limited technical-algorithmic literacy (antecedent, individual level) in sustaining employee trust and engagement (employee level), but not in correcting technically invalid algorithmic outputs (decision validity, organisational level). This partial compensation operates on the trust and engagement pathway, not on the decision-validity pathway.

*Rival mechanism: * The apparent compensation effect could reflect a ceiling effect (technical-algorithmic literacy has too little variance in low-infrastructure settings to show an independent effect) rather than genuine compensatory dynamics. P3 would be falsified if relational-cultural competence showed no compensatory effect on trust and engagement in low-infrastructure environments after accounting for variance restrictions in technical-algorithmic literacy.

Proposition 4. In SSA institutional environments where fewer than 18% of countries have reached the most advanced ICT regulatory tier (ITU G4, used as a proxy for broader institutional capacity; country level), the standardised effect of the focal HR professional's ethical-regulatory knowledge (antecedent, individual level) on PM governance effectiveness (organisational level) is larger than in institutional environments with mature governance scaffolding.

*Rival mechanism: * The larger effect could reflect unmeasured differences in HR professional selection or training between institutional tiers rather than institutional-void internalisation. P4 would be falsified if ethical-regulatory knowledge showed equal or lower standardised effects in weakly regulated environments compared with strongly regulated ones after controlling for professional selection and training differences.

Proposition 5. The positive relationship between AI-augmented PM system adoption (organisational level) and employees' procedural and interactional justice perceptions (employee level) is moderated by the focal HR professional's algorithmic interpretive competence (individual level), such that the relationship is positive when AIC is high and nonsignificant or negative when AIC is low.

*Rival mechanism: * The moderation effect could be driven by overall HR service quality rather than AIC specifically; AIC-high professionals may simply be better HR professionals across all dimensions. P5 would be falsified if the interaction term (adoption x AIC) did not significantly predict justice perceptions, i.e., if the adoption-to-justice relationship were invariant across levels of interpretive competence, or if the interaction effect disappeared after controlling for overall HR service quality.

Read together, the five propositions describe a coherent causal structure, summarised visually in **Figure 2** and in tabular form in **Table 3**. Proposition 1 establishes that the antecedent (technical-algorithmic literacy) is an entry condition, not an outcome-producing condition, for effective PM governance. Propositions 2a, 2b and 2c specify how three distinct institutional-void dimensions, regulatory, skills and technical infrastructure, amplify the practical stakes of contextual-interpretive competence once external scaffolding is absent along each dimension. Proposition 3 identifies relational-cultural competence as a partial substitute mechanism operating on a specific pathway (trust and engagement) under specific conditions (constrained infrastructure), explicitly not contradicting P1 because the compensation operates on a different outcome pathway than the one P1 addresses (governance effectiveness broadly). Proposition 4 connects the antecedent's (ethical-regulatory knowledge) marginal contribution to the institutional-voids context. Proposition 5 closes the loop by connecting the competency construct back to the employee-facing justice outcomes. The temporal logic across all five is that AIC is a pre-existing or co-developing capacity that shapes outcomes once an AI-augmented PM system is adopted, not a mediating consequence of adoption itself. A single cross-cutting boundary condition applies: each proposition assumes an organisational context in which some form of AI-augmented PM system has already been adopted. The propositions are silent on the prior question of whether adoption itself is advisable under conditions of severe institutional void.

Propositional Model: AIC, Institutional Voids, and PM Governance Outcomes

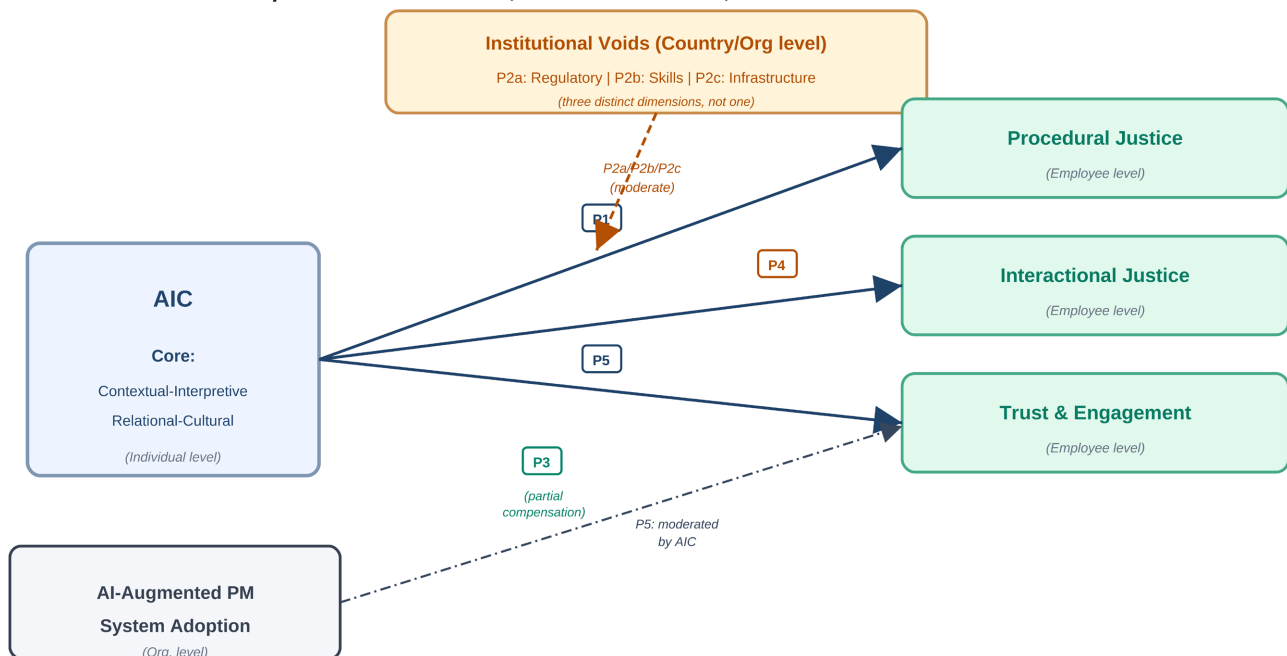


Figure 2. Propositional model: AIC, institutional voids, and PM governance outcomes.

Solid arrows represent direct relationships (P1, P5); the dashed arrow represents moderation by the three institutional-void dimensions (P2a, P2b, P2c) and by P4; the dash-dot arrow represents the partial-compensation pathway (P3).

Table 3. Propositions summary: predictors, mechanisms, boundary conditions, outcomes and levels of analysis.

Prop.	Predictor(s)	Mechanism	Boundary Condition	Measurable Outcome	Level(s) of Analysis
P1	Technical-algorithmic literacy (antecedent) jointly with contextual-interpretive competence (core)	Conditional/joint effect: antecedent predicts outcome only with the core competence present	Organisations that have adopted an AI-augmented PM system	PM governance effectiveness	Individual (predictors); Organisational (outcome)
P2a	Contextual-interpretive competence x national AI regulatory maturity	Weak regulatory frameworks strengthen the competence-to-justice relationship	ITU G4 regulatory maturity below Tier 4	Employees' procedural-justice perceptions	Individual x Country → Employee
P2b	Contextual-interpretive competence x organisational AI skills infrastructure	Limited training/competency-development availability strengthens the same relationship	Organisation-level skills infrastructure	Employees' procedural-justice perceptions	Individual x Organisation → Employee
P2c	Contextual-interpretive competence x technical/connectivity infrastructure	Limited technical infrastructure strengthens the same relationship, independently of P2a/P2b	Country- or organisation-level infrastructure (Section 2.3)	Employees' procedural-justice perceptions	Individual x Country/Organisation → Employee
P3	Relational-cultural competence (core)	Partial compensation for limited technical-algorithmic literacy on the trust/engagement pathway only	Constrained technical infrastructure (Section 2.3)	Employee trust and engagement (not decision validity)	Individual → Employee
P4	Ethical-regulatory knowledge (antecedent)	Standardised effect on governance effectiveness is larger under weak institutional scaffolding	ITU G4 < Tier 4 (proxy for institutional capacity)	PM governance effectiveness	Individual (predictor); Country (boundary); Organisational (outcome)
P5	AI-augmented PM system adoption x AIC	Moderation: adoption-to-justice relationship positive when AIC high, weak/negative when low	System already adopted (general boundary condition)	Procedural and interactional justice perceptions	Organisational (adoption) x Individual (AIC) → Employee

All cells extracted directly from each proposition's existing wording; no new content invented for this table.

6. Discussion

6.1. Theoretical Contributions

This paper makes three contributions to the HRM literature on artificial intelligence. First, it introduces algorithmic interpretive competence as a bounded construct, defined as contextual interpretation and professional judgement applied to algorithmic PM outputs, distinguished from adjacent constructs (AI literacy, algorithmic literacy, ethical competence, cultural intelligence, HR professional judgement, human-AI collaboration competence) through a construct-comparison matrix (Table 1) that specifies shared, excluded and added attributes for each. Second, it develops a framework that maps AIC onto the stages of a canonical PM cycle (Table 2), thereby grounding the construct in specific governance tasks rather than abstract dimensional labels. Third, it integrates institutional theory,

competence theory, algorithmic literacy scholarship, algorithmic-control theory and Ubuntu relational philosophy into a coherent multi-tradition architecture in which each tradition performs distinct, non-substitutable explanatory work. This architecture responds directly to a documented weakness in AI-HRM scholarship, the tendency towards theoretical over-stacking, not by minimising the number of theoretical traditions invoked but by ensuring each one passes a parsimony test: institutional theory (Section 2.3) explains why identical technology generates different competency demands across settings; competence-in-action theory (Section 2.4) explains what “having” the right knowledge means for situated interpretive work; algorithmic literacy scholarship (Section 2.2) specifies what “reading” an algorithm involves; the algorithmic-control and duality-of-management literature (Kellogg et al., 2020; Duggan et al., 2020; Meijerink & Bondarouk, 2023; Keegan & Meijerink, 2025) supplies the organisational-control vocabulary the “contest” component of AIC requires and that no other tradition in this list provides; and Ubuntu relational philosophy (Mangaliso, 2001; Mbiti, 1990) grounds the relational-cultural dimension as a normative resource rather than a residual category, doing work none of the other four traditions can do. Five traditions, not three, but each earns its place by answering a question the others cannot.

The parsimony argument above establishes that each tradition is necessary; it is a separate claim, addressed here, that the five combine into one coherent architecture rather than remaining five parallel defences. Read as a functional division of labour, institutional theory and the institutional-voids literature set the boundary conditions under which the whole framework operates, they specify when and where the other four traditions’ work becomes more or less consequential (Section 2.3; Propositions 2a, 2b and 2c). Competence-in-action theory supplies the individual-level content of what competency is and how it is acquired or exercised, the vocabulary in which all four components of Section 4 are themselves defined. Algorithmic literacy scholarship supplies the epistemic vocabulary specifically for the technical-algorithmic antecedent, which means to read an algorithmic output correctly before any interpretation of that output begins. Algorithmic-control and duality-of-management theory supplies the vocabulary for contestation and override, the “contest” verb in AIC’s definition and the ethical-regulatory antecedent’s compliance-judgement work depend on this tradition’s account of how algorithmic authority can be legitimately challenged. Ubuntu relational philosophy supplies the normative logic specifically for the relational-cultural core dimension, the standard against which a communication of an algorithmic output counts as dignifying rather than merely accurate. No two traditions do the same job in this architecture: each is tied to a distinct component or boundary condition rather than offering a competing general account of the whole framework, which is what distinguishes this five-tradition structure from the kind of undifferentiated theoretical accumulation the parsimony test above is designed to rule out.

Table role summary. Institutional theory and institutional voids sets boundary conditions (Section 2.3; Propositions 2a-2c). Competence-in-action theory supplies individual-level competency content (Section 4, all four components). Algo-

rhythmic literacy scholarship supplies epistemic vocabulary for the technical-algorithmic antecedent (Section 4.4). Algorithmic-control and duality theory: supplies vocabulary for contestation and override (Section 4.8's "contest" verb; ethical-regulatory antecedent). Ubuntu relational philosophy supplies normative logic for the relational-cultural core dimension (Section 4.3).

6.2. Practical Implications for HR Development in Sub-Saharan Africa

The framework suggests that curricula for HR training programmes, whether delivered by universities, professional bodies or employers, should treat contextual-interpretive and relational-cultural competence as core content rather than as elective supplements to technical AI training. The framework also suggests that, under institutional voids, the interpretive and relational dimensions may carry a larger share of the governance and trust burden than the technical antecedent, but empirical validation, including comparative studies across institutional settings and training-intervention evaluations, is needed before such claims about relative weights can be treated as established findings. The evidence that 95% of CHROs surveyed by Gartner had adopted AI by the end of 2025 while nearly three-quarters of HR leaders report only moderate or minimal returns (Gartner, 2026b) indicates that further investment in tool access alone is unlikely to close the value gap, whereas investment in interpretive and relational capability building may do so. For professional bodies and policymakers in SSA, particularly in the majority of countries where AI-specific regulatory scaffolding remains absent or nascent (only 18% at the most advanced ICT regulatory tier; International Telecommunication Union, 2025, noting that this is a proxy for broader institutional capacity), professional associations such as national HR institutes have a comparatively larger role to play in establishing normative standards for algorithmic PM practice than their counterparts in more heavily regulated jurisdictions.

The framework also implies a sequencing logic for organisations designing AI-augmented PM rollouts. Technical algorithmic literacy (the antecedent) is a prerequisite that should be established first, since interpretive judgement cannot be exercised over an output a professional does not understand technically. Contextual-interpretive and relational-cultural competence, by contrast, are unlikely to transfer through classroom instruction alone; Sandberg's (2000) interpretive account of competence as situated meaning-making suggests that these dimensions develop through supervised practice, case-based coaching and structured reflection on actual PM decisions. Ethical-regulatory knowledge sits between the two: it can be partly codified through organisational policy and decision-rights protocols, but its exercise in specific cases still depends on judgement that codification alone cannot supply.

6.3. Limitations and Future Research Directions

This is a conceptual paper, and the framework it proposes requires empirical val-

validation before its propositions can be treated as established findings. Six specific limitations should be noted. First, a complete PRISMA-style screening record was not maintained during the original literature search and cannot be reconstructed; the search architecture documented in Section 3 is a post-hoc rationalisation of the review logic rather than a contemporaneous record, which limits the review's reproducibility. Second, the search was restricted to English-language sources indexed in Scopus and Web of Science, introducing language and database biases that may systematically exclude relevant Francophone, Lusophone and indigenous-language scholarship from SSA. Third, a substantial share of the quantitative evidence cited in Sections 2 and 4 comes from unreviewed commercial sources (Gartner, Deloitte, McKinsey, Betterworks, Worklytics); these are identified as such throughout, but their use as descriptive evidence rather than as inputs to peer-reviewed analytical claims remains a limitation. This reliance should be moderated as the peer-reviewed literature on AI-augmented performance management matures: several of the industry statistics cited here (adoption rates, perceived value, training coverage) are precisely the kind of finding that academic survey research is well placed to superset with instrumented, validated measures, and future revisions of this framework should substitute peer-reviewed replications wherever they become available rather than treating the current industry-report base as a stable evidentiary foundation. Fourth, no primary empirical study of AI-augmented performance management in SSA organisations is cited in this paper. The framework is prospective: it draws on secondary SSA evidence (published empirical studies from South Africa and a regional systematic review) and cross-country institutional data (ITU, AfriCatalyst) to contextualise and illustrate claims that are ultimately theoretically derived. Primary data collection, whether through validated scale development for AIC or through qualitative studies of how HR professionals actually navigate AI-augmented PM systems in SSA organisations, would substantially strengthen the framework's empirical footing. Fifth, the construct-comparison matrix (**Table 1**) identifies overlap with adjacent constructs but does not empirically discriminate AIC from them; that discrimination requires scale development and discriminant-validity testing. Sixth, the review was conducted by a single author without a second reviewer or inter-coder reliability check.

Future research should prioritise four directions: development and validation of a psychometric scale for AIC, paralleling the AI-literacy scale work of [Yuan et al. \(2024\)](#) but specified for the PM governance role; comparative studies that test the institutional-voids moderation proposed in Propositions 2a, 2b and 2c across countries with varying regulatory maturity within SSA (e.g., South Africa vs. lower-income economies); longitudinal research tracking how AIC develops, or fails to develop, as HR professionals gain experience with AI-augmented PM systems over time; and training-intervention studies that evaluate whether the sequencing logic proposed in Section 6.2 produces better PM governance outcomes than undifferentiated AI training.

7. Conclusion

Artificial intelligence has moved from administrative convenience to a co-producer of performance judgements, and it has done so faster than the HR profession's capacity to govern it responsibly has developed. The evidence marshalled in this paper, near-universal AI adoption among CHROs alongside a reported 8% of HR leaders believing their managers have the skills to use AI effectively (Gartner, 2025a), suggests that the gap is not primarily one of access or even of data literacy narrowly defined, but of a broader interpretive capacity that existing frameworks do not name. Algorithmic interpretive competence, defined as the contextual interpretation and professional judgement applied to algorithmic PM outputs, with technical-algorithmic literacy and ethical-regulatory knowledge as antecedents and organisational governance as an enabling condition, offers a way to specify what that capacity consists of and why its requirements shift under the institutional conditions that characterise much of Sub-Saharan Africa. The construct is bounded: it does not encompass general AI literacy, organisational-level AI governance, or the full range of HR professional competence. Its core, contextual-interpretive and relational-cultural competence, is what makes the difference between an AI-augmented PM system that delivers procedurally just and interactionally dignifying outcomes and one that merely delivers faster, more opaque versions of the failures PM systems have long been criticised for. Responsible AI governance in emerging economies will depend, in no small part, on whether the HR profession builds this interpretive competence deliberately or is left to acquire it by trial and error. The framework proposed here is deliberately partial: it specifies what AIC consists of and why its components matter more, or differently, under institutional voids, but it does not by itself guarantee that organisations will invest in building it. That remaining task, translating a conceptual framework into curricula, organisational practice and formal standards, is the applied agenda this paper leaves for the research and practice communities it addresses.

Conflicts of Interest

The author declares no conflict of interest. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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Appendix

Table A1. Source-by-code evidence matrix.

#	Source	Coding Category	Competency Dimension(s)	SSA-Specific	Source Type
1	AfriCatalyst (2025)	Institutional	General	Yes	Industry/institutional report
2	Annapureddy et al. (2025)	Epistemic	Ant-TAL	No	Peer-reviewed
3	Betterworks (2026)	Epistemic	D1-CI	No	Industry/institutional report
4	Boyatzis (1982)	Competence	General	No	Book
5	Budhwar et al. (2023)	Epistemic	General	No	Peer-reviewed
6	Budhwar et al. (2022)	Epistemic	General	No	Peer-reviewed
7	Cetindamar et al. (2024)	Epistemic	Ant-TAL	No	Peer-reviewed
8	CIPD (2024)	Competence	General	No	Practitioner framework
9	Chowdhury et al. (2024)	Epistemic	General	No	Peer-reviewed
10	Chowdhury et al. (2023)	Epistemic	EC	No	Peer-reviewed
11	Coetzee et al. (2025)	Competence	D2-RC	Yes	Peer-reviewed
12	Deepa et al. (2024)	Competence	General	No	Peer-reviewed
13	Deloitte (2024)	Epistemic	D1-CI	No	Industry/institutional report
14	Deloitte (2025)	Epistemic	D1-CI/D2-RC	No	Industry/institutional report
15	DiMaggio & Powell (1983)	Institutional	General	No	Peer-reviewed
16	Duggan et al. (2020)	Epistemic	D1-CI	No	Peer-reviewed
17	Gartner (2025a)	Epistemic	Ant-TAL	No	Industry/institutional report
18	Gartner (2025b)	Epistemic	Ant-TAL	No	Industry/institutional report
19	Gartner (2025c)	Epistemic	D2-RC	No	Industry/institutional report
20	Gartner (2026a)	Epistemic	General	No	Industry/institutional report
21	Gartner (2026b)	Epistemic	D1-CI/Ant-TAL	No	Industry/institutional report
22	ITU (2025)	Institutional	General/P2a, P2c	Yes	Industry/institutional report
23	Keegan & Meijerink (2025)	Epistemic	D1-CI	No	Peer-reviewed
24	Kellogg et al. (2020)	Epistemic	D1-CI/EC	No	Peer-reviewed
25	Khanna & Palepu (2010)	Institutional	General	No	Book
26	Kim et al. (2024)	Epistemic	EC	No	Peer-reviewed
27	Konjen (2025)	Epistemic	D1-CI	No	Preprint

Continued

28	Le Boterf (2011)	Competence	General	No	Book
29	Liu et al. (2024)	Epistemic	D1-CI	No	Peer-reviewed
30	Mangaliso (2001)	Institutional / Competence	D2-RC	Yes	Peer-reviewed
31	Mbiti (1990)	Institutional / Competence	D2-RC	Yes	Book
32	McClelland (1973)	Competence	General	No	Peer-reviewed
33	McKinsey & Company (2025a)	Institutional	General	Yes	Industry/institutional report
34	McKinsey & Company (2025b)	Institutional	General	No	Industry/institutional report
35	Meijerink & Bondarouk (2023)	Epistemic	D1-CI	No	Peer-reviewed
36	Moharrak et al. (2024)	Institutional	General	Yes	Peer-reviewed
37	North (1990)	Institutional	General	No	Book
38	Owor et al. (2025)	Institutional / Epistemic	General/P2b	Yes	Peer-reviewed
39	Poisat et al. (2024)	Competence	D2-RC	Yes	Peer-reviewed
40	Prikshat et al. (2023)	Epistemic	General	No	Peer-reviewed
41	Sandberg (2000)	Competence	D1-CI	No	Peer-reviewed
42	Scott (2014)	Institutional	General	No	Book
43	SHRM (2025)	Competence	Ant-TAL	No	Practitioner framework
44	SHRM (2026)	Epistemic	Ant-TAL	No	Industry/institutional report
45	Spencer & Spencer (1993)	Competence	General	No	Book
46	Tandon et al. (2025)	Epistemic	D1-CI	No	Peer-reviewed
47	Tong et al. (2021)	Epistemic	D1-CI	No	Peer-reviewed
48	Torraco (2005)	Methodology	N/A	No	Peer-reviewed
49	Torraco (2016)	Methodology	N/A	No	Peer-reviewed
50	Ulrich & Dulebohn (2015)	Competence	General	No	Peer-reviewed
51	Van Vulpen & Veldsman (2022)	Competence	General	No	Practitioner framework
52	Worklytics (2025)	Epistemic	D1-CI	No	Industry/institutional report
53	WEF (2025)	Epistemic	Ant-TAL	No	Industry/institutional report
54	Yuan et al. (2024)	Epistemic	Ant-TAL	No	Peer-reviewed

Note: Torraco (2005) and Torraco (2016) jointly constitute the review methodology; the manuscript's stated count of 53 sources treats them as a single methodological entry. Coding categories: Institutional, Competence, Epistemic (Section 3.3). Dimension abbreviations: D1 - CI = Contextual-Interpretive Competence; D2 - RC = Relational-Cultural Competence; Ant-TAL = Technical-Algorithmic Literacy (antecedent); Ant-ERK = Ethical-Regulatory Knowledge (antecedent); EC = Enabling Conditions; General = not dimension-specific.