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The Misattribution of Employee Performance When AI-Generated Outputs Conceal Human Verification, Exception Handling, and the Repair of Automated Errors

Aisha Rahman[1*], Laura Fitzgerald[2], Daniel Okoro[3], Grace Okafor[4]

Abstract

Generative and algorithmic systems increasingly participate in tasks whose outputs enter employee performance evaluation. Yet the visibility of AI-associated output is often greater than the visibility of the human work required to verify, contextualize, reject, escalate, or repair that output. This article develops a mechanism-based account of how that asymmetry can distort employee performance attribution. The argument distinguishes observable task output from the less observable assurance activities through which employees make AI-supported work usable, safe, and contextually appropriate. Misattribution is theorized to arise when evaluators infer employee contribution from an incomplete set of cues and cannot reconstruct the division of labour between employee and system. Crucially, the mechanism is not unidirectional. Hidden human verification and repair can produce under-credit, whereas machine-associated performance can also be psychologically transferred to the employee and produce over-credit. The article therefore treats attribution as conditional on task-frontier position, traceability of human intervention, evaluator knowledge, human–AI agency configuration, and the design of performance-management systems. It develops the basis for a Human Contribution Visibility Framework and later derives HRM propositions concerning when apparently similar AI-supported outputs should generate different evaluation and reward consequences. The central implication is that final output becomes an unreliable indicator of employee contribution when consequential assurance and repair activity is systematically less observable than the output it makes possible.

Keywords Exception handling, AI-augmented work, Employee performance attribution, Verification labour, Algorithmic performance management, Human contribution visibility

*Correspondence:
Aisha Rahman
aisha.rahman@lums.edu.pk
[1] Department of Human Resource Management, Lahore University of Management Sciences, Lahore, Pakistan
[2] Department of Management, University College Dublin, Dublin, Ireland
[3] Department of Business Administration, University of Lagos, Lagos, Nigeria
[4] Department of Business Administration, University of Ibadan, Ibadan, Nigeria

Introduction

Generative artificial intelligence and algorithmic technologies are changing how organizations allocate work, monitor performance, and make HR decisions [1, 2]. Their significance for performance management does not arise only from automation. AI systems increasingly participate in tasks whose completed outputs are visible to managers even when the distribution of human and machine contribution behind those outputs is difficult to reconstruct.

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This creates a specific attribution problem. Experimental and field evidence shows that supervisors can attribute robot-associated performance to employees and consequently inflate employee ratings [3]. Research on AI-enabled appraisal likewise shows that employees respond differently to appraisal arrangements depending on AI characteristics and the distribution of decision authority between human and technological actors [4]. These findings indicate that the presence of AI does not simply add another performance input. It changes the informational environment from which judgments about employee contribution are made.

At the same time, AI-supported work contains human activities that are poorly represented by the final output. Employees may prepare data, interpret model results, reconcile outputs with situational knowledge, exercise value judgments, detect exceptions, reject unsuitable recommendations, and correct errors. Such activities have been described as data, knowledge, and values work that continues around apparently autonomous AI systems [5]. Their relevance to performance attribution is theoretically important because mechanisms cannot be established by observing that AI use and evaluation outcomes co-vary; explanation requires identifying the entities, activities, and conditions through which an outcome is produced [6]. Broader HRM scholarship on generative AI similarly emphasizes that AI adoption redistributes rather than simply eliminates human work and managerial responsibility [7].

The problem examined here is therefore narrower than whether AI raises employee productivity, whether algorithmic management increases control, or whether AI-based appraisal is accepted by employees. The question is how evaluators attribute performance when visible AI-associated outputs coexist with human contribution that is less observable because it consists partly of verification, exception handling, and error repair. A mechanism-based analysis is necessary because identical-looking outputs can arise from different underlying divisions of labour, while similar human effort can produce different visible outcomes depending on the reliability of the AI system and the difficulty of the task. The following sections first clarify the attribution environment, then separate visible output from hidden contribution before specifying the forms of assurance and repair work that can disappear from conventional performance evidence.

Employee Performance Attribution in AI-Augmented Work

Performance attribution in AI-augmented work occurs inside systems that already shape which behaviours are observed and how those behaviours are interpreted. Employees can perceive algorithmic HR systems as mechanisms of managerial control or as sources of useful feedback, and those interpretations are associated with different motivational, behavioural, and well-being consequences [8]. Algorithmic management itself is multidimensional: monitoring, goal setting, scheduling, performance rating, and compensation can be allocated partly to computational systems rather than human managers [9]. Platform research further shows that workers distinguish commitment-oriented from control-oriented algorithmic practices and that transparency can change the consequences of those interpretations [10].

These findings concern how workers interpret systems. Performance attribution introduces a different but related inferential problem: how evaluators interpret employee contribution when a system has participated in production. Human managers remain important within algorithmic performance-management arrangements because they can interpret, contextualize, question, or correct system-generated assessments [11]. Perceptions of AI agency provide another pathway, because observers may respond differently when the technology is understood as possessing substantial independent capacity rather than functioning as an instrument of human action [12].

The evaluative environment is also shaped by how strongly algorithms record, recommend, restrict, rate, reward, or replace human activities [13]. Platform work demonstrates the extreme case, in which app-mediated systems can simultaneously structure labour processes and produce the metrics through which workers are assessed [14]. Even within such settings, however, algorithmic evaluation does not generate uniform performance consequences; worker experience and the challenges embedded in gig work can alter the pathway between evaluation and service performance [15]. Trust research reinforces this conditionality because human responses to AI vary with system characteristics, task conditions, reliability, embodiment, and user perceptions [16].

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For this article, these literatures establish an important boundary. An evaluator cannot be assumed to observe employee contribution directly merely because output, system logs, or algorithmic ratings are available. Such evidence is filtered through assumptions about what the AI did, what the employee controlled, what failures were possible, and what kinds of intervention were necessary. Employee performance attribution in AI-augmented work is consequently an inference from incomplete and selectively visible cues.

Visible AI Output and Invisible Human Work

The final output of AI-supported work is an especially powerful but potentially ambiguous cue. Field evidence demonstrates that generative AI can improve performance within some task regions while producing weaker or adverse effects when tasks fall outside the technology's effective frontier; productivity effects also vary across worker experience, task type, and forms of collaboration [17–19]. Visible output therefore cannot be treated as a stable indicator of the proportion of value produced by the employee.

The ambiguity becomes greater when human and technological agency are intertwined. Generative AI can create configurations in which human and machine agency are distributed across production, interpretation, selection, and revision rather than cleanly assigned to one actor [20]. This is consistent with the broader automation–augmentation paradox: automation of some activities can increase the importance of complementary human activities elsewhere in the same workflow [21]. Learning algorithms similarly change how knowledge and coordination are organized [22], while organizational studies show that algorithmic systems can alter which forms of expertise appear legitimate or authoritative [23]. Research on AI adoption in recruitment likewise describes human and AI agency as jointly constituted through organizational structures and practices [24].

The attributional difficulty is therefore not simply that AI performs part of a task. It is that different contributions leave different evidentiary traces. Generated text, recommendations, classifications, scores, and completed transactions are usually visible. By contrast, the employee's rejected AI outputs, detected inconsistencies, contextual corrections, silent checks, and decisions not to rely on the system may leave little comparable evidence. A successful intervention can be particularly difficult to credit when its observable result is merely that no error occurred.

This asymmetry creates the precondition for performance misattribution. The same visible result may reflect very different amounts of human judgment and assurance, while different visible results may occur despite similar human effort because the underlying AI performs unevenly across tasks. The relevant theoretical object is therefore the relationship among visible output, latent human assurance contribution, and the cues available to the evaluator.

The interaction among these elements is represented in **Figure 1.**

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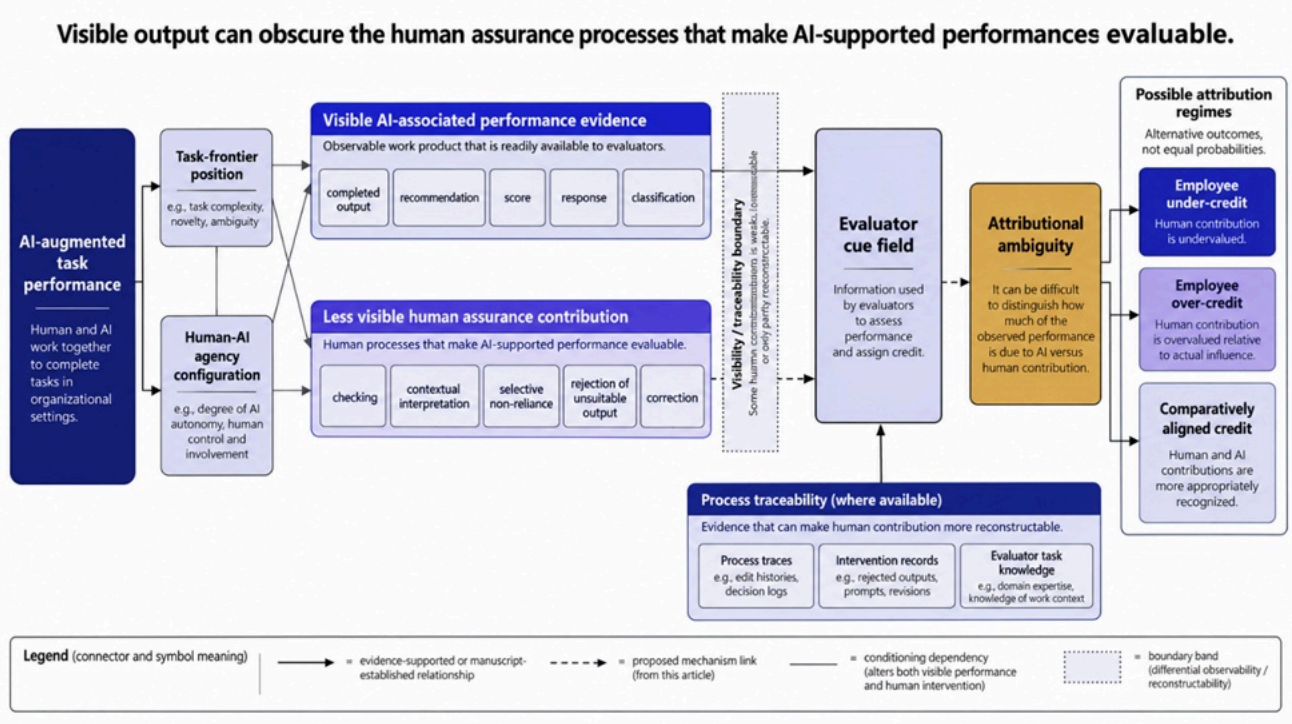


Figure 1. Visible output can obscure the human assurance processes that make AI-supported performance evaluable

Verification Labour

Verification labour begins where an employee must decide whether an AI output is sufficiently credible, relevant, and contextually appropriate to be used. Studies of professionals working with opaque AI demonstrate that competent use involves active judgment about when to engage the system, when to rely on its output, and when local knowledge should override or qualify the recommendation [25]. Experimental work on human–AI delegation similarly shows that productive allocation of work depends on knowing the relative strengths and weaknesses of both the person and the AI system [26].

Verification therefore cannot be reduced to checking whether an output exists or appears plausible. It can include assessing source quality, testing internal consistency, comparing an output with domain knowledge, recognizing when a task falls outside the system's competence, and deciding whether a recommendation should be accepted, modified, rejected, or escalated. These activities may occur before any visible failure and therefore generate value through prevention.

The scope of assurance can also extend beyond the immediate output. Research on generative-AI risk work shows that concentrating only on users and local routines can overlook risks originating in data, models, infrastructure, deployment choices, and broader technological ecosystems [27]. More generally, AI systems combine varying degrees of autonomy, learning, and inscrutability, creating management problems that differ from those associated with conventional information technologies [28]. Verification labour is consequently distributed across multiple objects of attention: the output, the task context, the system's known limitations, and the organizational conditions under which the output will be used.

For performance attribution, the critical point is that verification is often valuable precisely when it prevents observable failure. An employee who identifies a problematic recommendation before implementation may leave less visible evidence of contribution than an employee who repairs an error after it becomes consequential. This creates a temporal asymmetry between preventive contribution and observable outcome.

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The different assurance activities can therefore be distinguished by what they inspect, what triggers them, and what kind of contribution trace they are likely to leave.

Table 1 presents the analytical distinctions discussed here.

Table 1. Assurance activities differ in when human contribution becomes visible during AI-supported work

Assurance activity	Immediate object of judgment	Typical trigger	Human contribution before visible failure	Likely observable trace	Transition if the issue is not resolved
Output plausibility checking	AI-produced answer, prediction, recommendation, or classification	Output appears incomplete, inconsistent, unusual, or insufficiently supported	Detecting whether the result is credible enough to use	May be weak if checking confirms the output and no change is recorded	Escalation to deeper contextual or technical review
Context reconciliation	Fit between AI output and task-specific or organizational circumstances	Output is technically plausible but may not fit local facts, constraints, or goals	Integrating situated knowledge unavailable to the system	Moderate when revisions are documented; weak when judgment remains tacit	Modification, rejection, or exception handling
Capability-boundary testing	Whether the task lies within a domain where AI assistance is dependable	Novel, ambiguous, high-stakes, or atypical task conditions	Recognizing limits of system competence and avoiding inappropriate reliance	Often weak because the principal result is non-use or selective reliance	Alternative human process or specialist escalation
Selective acceptance and rejection	Which parts of AI output should enter the final work product	Mixed-quality or partially correct output	Separating usable material from misleading or unsupported material	Variable; visible only when edits, rejected alternatives, or decision logs are retained	Correction or reconstruction of defective components
Preventive correction	Detectable defect before downstream use	Verification reveals an error with potential operational consequences	Repairing an error before it becomes externally visible	Potentially low because successful prevention removes the observable failure	No visible incident, or later exception handling if correction is incomplete

Exception Handling and Error Repair

Verification becomes exception handling when the employee encounters a condition that cannot be resolved through routine acceptance, rejection, or local correction. The problem may originate in the data, model, deployment

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configuration, or organizational process surrounding the AI system. Research on AI-driven HRM demonstrates that bias-management capability itself can be decomposed across data, model, and deployment stages, indicating that apparently similar problems may require intervention at different technical and organizational locations [29].

The employee's role in such situations should not be modelled as passive compliance with an algorithm. Critiques of algorithmic-management research show that overly simplified assumptions about workers can obscure adaptation, interpretation, resistance, and contextual judgment [30]. Exception handling therefore includes deciding what kind of failure has occurred, whether the problem can be locally corrected, whether the AI output should be abandoned, and whether a broader technical or managerial intervention is required.

This work can carry performance costs that are difficult to separate from the quality of the underlying AI. Mixed-method research on algorithmic management documents adverse behavioural consequences under some conditions [31], while qualitative research with HR professionals finds simultaneous appreciation, aversion, and uncertainty toward algorithmic HRM [32]. Such evidence cautions against treating error handling as a uniform burden or assuming that employees and evaluators interpret problematic AI behaviour in the same way.

A mechanism-based account therefore distinguishes at least three events: the appearance of an anomalous or defective output, the human activity used to diagnose or repair it, and the subsequent attribution of the final performance result. These events can be temporally separated and differently visible. A repaired error may disappear from the final output even though the employee expended substantial expertise to remove it. Conversely, repeated visible corrections may make human contribution more salient precisely because the underlying system performs poorly.

The central theoretical problem emerges from this mismatch. Performance records often privilege what was delivered, how rapidly it was delivered, or whether a target was reached. They may capture neither the number of unsuitable AI outputs that were rejected nor the expertise required to detect them. When evaluators cannot reconstruct those interventions, output quality alone provides an incomplete basis for assigning performance credit. The next section therefore turns from the work itself to the mechanisms through which incomplete contribution evidence can produce different attributional outcomes.

Performance Misattribution Mechanisms

Algorithmic work design affects not only how employees perform tasks but also which parts of that performance become measurable. When algorithms allocate, monitor, and evaluate work, they can restructure autonomy, demands, feedback, and the informational traces available for subsequent assessment [33]. Qualitative evidence from app-mediated work similarly shows that algorithmic HRM control is produced through interacting technological and organizational actors rather than through a single automated evaluator [34]. These conditions matter because evaluators rarely observe the complete production process.

The proposed mechanism begins with visibility asymmetry. Visible output provides an accessible cue, whereas verification, selective rejection, contextual correction, and successful prevention may leave weaker traces. Evaluators then infer employee contribution from this unequal evidence. Where assurance activity is consequential but weakly traceable, employee contribution may be understated. Yet the reverse is also possible: machine-associated performance can be transferred psychologically to the employee, producing inflated ratings [3]. Misattribution therefore denotes a mismatch between inferred and underlying contribution, not a predetermined downward bias.

This mechanism should weaken when intervention records, evaluator expertise, or work processes make the division of human and AI contribution reconstructable. It should also weaken where AI involvement is minimal or where output itself reliably reflects employee contribution. Conversely, ambiguity should increase when tasks lie near uncertain AI capability boundaries, when agency is jointly configured, or when the evaluator has little knowledge of the assurance work necessary to obtain the observed result [17]. Trust, perceived AI agency, control-oriented interpretations, and managerial

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reflexivity provide competing pathways capable of producing similar evaluation patterns [11]. The theory consequently predicts conditional attribution regimes rather than a universal consequence of AI use.

Human Contribution Visibility Framework

AI can alter both how employees create value and how that value is subsequently captured or recognized [35]. Building on this distinction, the Human Contribution Visibility Framework is proposed as a way to identify when employee contribution to AI-supported performance is sufficiently observable for attribution. It is not presented as a validated measurement scale. Its analytical purpose is to separate the existence of human contribution from the evidence through which an evaluator can reconstruct that contribution.

Three features are central. Contribution traceability concerns whether consequential human interventions leave retrievable evidence. Diagnosticity concerns whether those traces identify meaningful human contribution rather than simply record activity. Attribution accessibility concerns whether the relevant evidence actually reaches the person or process assigning performance credit. A technically complete audit trail can therefore remain attributionally ineffective if evaluators cannot interpret it, whereas a small number of well-targeted intervention traces can be informative when they reveal judgment that materially changed the outcome.

The framework also distinguishes productive contribution from assurance contribution. An employee may create part of the visible deliverable, improve AI-generated content, prevent inappropriate output from entering the workflow, or repair a realized error. Treating these activities as interchangeable would obscure why equal-looking outputs can embody different human contributions.

The resulting visibility distinctions are summarized in **Table 2**.

Table 2. Human contribution becomes attribution-relevant through different visibility pathways in AI-supported work

Human contribution pathway	What the employee contributes	What may remain hidden in final output	Evidence that can make contribution reconstructable	Attribution risk when visibility is weak
Direct production	Content, judgment, analysis, or action incorporated into the completed work	Relative human share when AI also generates substantial material	Version history, task records, documented decision ownership	Human and AI production may be conflated
Verification	Evaluation of plausibility, reliability, relevance, and contextual fit	Successful checks that produce no visible modification	Review records, decision rationales, retained alternatives	Preventive expertise may receive little credit
Selective non-reliance	Decision to reject or bypass unsuitable AI assistance	Outputs deliberately not used	Rejection logs or documented escalation decisions	Valuable non-use may appear as absence of contribution
Exception handling	Identification and management of anomalous cases	Diagnostic effort preceding escalation or correction	Exception records, escalation traces, case annotations	Difficulty may be attributed to employee rather than system
Error repair	Correction or reconstruction of defective	Extent of remedial effort after the defect	Revision history, correction records, post-	Final quality may conceal substantial

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	AI-supported work	disappears	incident documentation	repair labour
Integrative judgment	Reconciliation of AI output with domain, organizational, or stakeholder constraints	Tacit reasoning connecting multiple information sources	Concise decision rationale or accountable approval trace	Final output may be misread as largely system-generated

HRM Propositions

The framework generates propositions that distinguish the focal mechanism from explanations based solely on productivity, trust, or algorithmic control.

Proposition 1. For comparable visible AI-supported outputs, weaker traceability of consequential human verification and repair will be associated with greater divergence between underlying human contribution and evaluator-attributed employee performance.

This proposition concerns the availability of contribution evidence rather than the amount of AI use. Its implication differs from a productivity explanation because two employees can achieve similar observable results while carrying different assurance burdens.

Proposition 2. The relationship between hidden assurance contribution and employee under-credit will be stronger when evaluators have limited knowledge of the focal task or of the AI system's capability boundaries.

Professional reliance on AI requires knowledge about when system output warrants acceptance or challenge [25]. Evaluators lacking comparable knowledge may interpret successful performance without recognizing the judgment required to produce it.

Proposition 3. Greater visibility of human intervention will not uniformly increase employee performance ratings; where observers otherwise transfer AI-associated performance to the employee, clearer attribution of machine contribution may reduce employee over-credit [3].

The same visibility intervention can therefore correct opposite forms of misattribution depending on the evaluator's initial inference.

Proposition 4. Attributional distortion will be greater where AI performance varies substantially across task conditions while evaluation systems rely predominantly on final-output indicators.

Heterogeneous AI performance across task frontiers makes output less diagnostic of the human effort needed to secure an acceptable result [17].

Proposition 5. Organizational arrangements that preserve diagnostically relevant intervention and exception traces will weaken the association between visibility asymmetry and performance misattribution when evaluators possess the authority and expertise to interpret those traces.

Trace generation alone is insufficient. The information must enter an evaluative process in which human managers can contextualize and, where necessary, challenge algorithmically structured evidence [11].

These propositions yield distinct attribution regimes rather than a single predicted effect, as shown in **Figure 2.**

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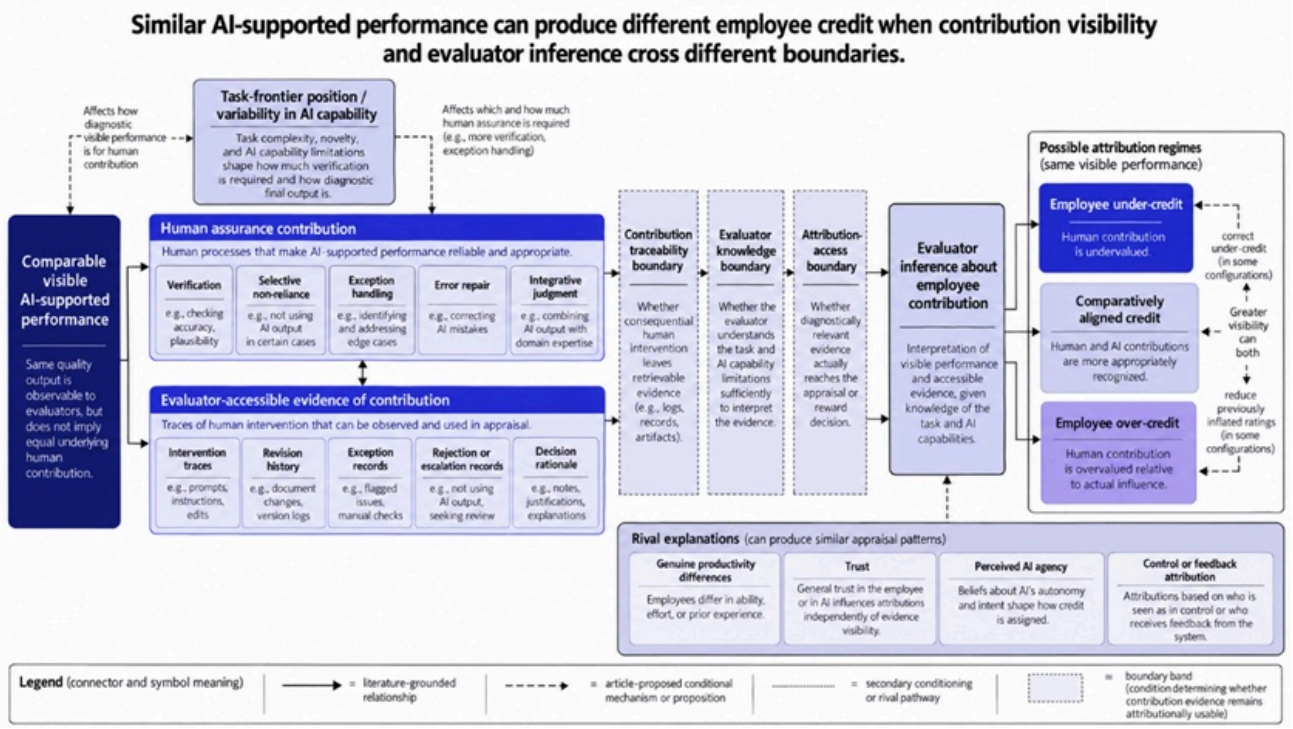


Figure 2. Similar AI-supported performance can produce different employee credit when contribution visibility and evaluator inference cross different boundaries

Evaluation and Reward Implications

Performance-management systems should therefore distinguish evidence of output from evidence of contribution. Increasing the quantity of monitoring is not a sufficient response. The relevant design problem is whether evaluation captures information that is diagnostically related to consequential employee judgment. Algorithmic systems already shape what is monitored, rated, and rewarded [9]; adding more low-value activity traces could intensify control without improving attribution.

Where AI-supported tasks contain substantial verification or repair requirements, organizations can instead preserve selective evidence of interventions that materially changed an outcome. Managerial review remains important because such traces require interpretation rather than mechanical counting [11]. Bias-management research likewise indicates that effective AI governance may require attention to data, model, and deployment conditions rather than attributing all observed problems to the employee operating the system [29].

Reward implications follow from the same logic. If AI changes the relationship between employee value creation and value capture [35], output-only evaluation can misallocate credit in either direction. HRM systems should therefore avoid presuming that visible AI-assisted productivity represents either independent employee performance or independent machine performance. The appropriate attribution depends on the contribution configuration that produced the result.

The practical implication is selective rather than universal: contribution-sensitive evaluation is most important where final output is weakly diagnostic of human contribution, AI reliability varies across tasks, and consequential human assurance is otherwise difficult for evaluators to reconstruct.

Conclusion

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AI-generated and AI-assisted outputs can conceal the human work that makes those outputs usable. The resulting performance-attribution problem arises when observable results and consequential human contribution leave unequal traces and evaluators must infer employee performance from that incomplete evidence.

The mechanism is conditional and bidirectional. Hidden verification, exception handling, and repair can leave valuable human contribution under-recognized, while AI-associated success can also be transferred to employees and inflate perceived performance. The theoretical issue is therefore not whether AI systematically diminishes employee credit, but when the visibility structure of AI-supported work prevents evaluators from distinguishing human contribution from machine-associated output.

The Human Contribution Visibility Framework identifies traceability, diagnosticity, and attribution accessibility as conditions connecting assurance work to performance evaluation. Its propositions predict that task-frontier position, evaluator knowledge, intervention evidence, and the organization of appraisal will determine whether comparable visible outputs produce under-credit, relatively aligned credit, or over-credit. Employee performance assessment in AI-augmented work is consequently most defensible when organizations evaluate not only what was visibly produced, but also whether the evidence available to evaluators permits a credible reconstruction of the human contribution that made the result possible.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 02 May 2025 Revised: 07 Jul 2025 Accepted: 24 Jul 2025
Published online: 18 March 2026

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