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Who Receives Credit for Effort in Technology-Mediated Organizational Work?

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Abstract

Technology-mediated work increasingly complicates a basic organizational question: who receives credit when valued outcomes arise from combinations of employee effort, technological capability, algorithmic coordination, and managerial interpretation? Existing research explains important parts of this problem through studies of digital visibility, algorithmic control, human–artificial intelligence collaboration, performance management, and technologically mediated judgment, yet these literatures do not provide an integrated account of how contribution becomes organizational recognition. This Original Conceptual Framework Article addresses that gap by proposing an Effort-Recognition Framework that separates contribution production from four subsequent processes: visibility, attribution, evaluative representation, and recognition allocation. The framework distinguishes human, technological, and joint contributions; identifies selective visibility and measurement compression as potential sources of recognition discrepancy; and treats managerial interpretation and contextual expertise as consequential parts of the recognition process rather than residual adjustments. It further proposes that task characteristics, technological opacity, expertise, organizational context, and the design of performance systems condition how contribution is interpreted. The article develops testable propositions concerning visibility selectivity, attribution partitioning, measurement-to-credit slippage, recognition discrepancy, and human contextual correction. It also identifies implications for motivation, identity, status, and organizational design. The framework is an original non-empirical synthesis rather than a validated causal model. Its relationships require direct empirical testing across occupations, technologies, organizational forms, and levels of analysis, particularly where digital traces are incomplete or human and technological contributions are difficult to disentangle.

Keywords: Visibility of human effort, Attribution between employees and technologies, Performance measurement and credit allocation, Effort-recognition framework, Credit, Effort

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Introduction

Organizations have long allocated recognition by interpreting who contributed to valued outcomes, yet technologically mediated work makes that interpretation increasingly difficult. Learning algorithms can reshape expertise, quantification, organizational boundaries, and the conditions under which work becomes knowable to others [1]. Algorithmic systems may also record, rate, recommend, restrict, replace, or reward workers, embedding technological mediation directly within mechanisms of organizational control [2]. The recognition problem is therefore not limited to whether technology improves performance. It concerns how organizations infer contribution when productive activity, evaluative information, and managerial judgment are distributed across employees, systems, and their interaction.

A simple human-versus-technology framing is inadequate because automation and augmentation are not necessarily independent alternatives. Their relationship can be paradoxical: systems that automate portions of work can simultaneously increase demands for human judgment, coordination, oversight, or complementary expertise [3]. Digital transformation likewise produces configurations in which human and technological activities are intertwined, including forms of consequential work that may be difficult to observe from final outputs alone [4]. Consequently, a technologically generated result cannot by itself reveal how much employee effort preceded it, which human contributions made it usable, or whether an apparently automated outcome depended on substantial contextual or corrective work.

Recognition also cannot be reduced to a technical accounting problem. Digital technologies alter job demands, resources, autonomy, and other characteristics of work design, meaning that the organizational setting in which contribution is produced also changes [5]. Human reliance on artificial intelligence is similarly contingent rather than automatic; trust varies with properties of the technology, task, representation, and user [6]. These literatures imply that identical outputs may be interpreted differently depending on who or what is believed to have produced them, how the work became visible, and which evaluative system translated performance into organizational judgment.

This article develops an original conceptual framework for explaining that translation. It defines effort recognition as the organizational process through which contributions interpreted as relevant to an outcome become associated with acknowledgment, rewards, opportunities, reputation, status, or responsibility. The central proposition is not that employees should invariably receive more credit than technologies, nor that invisible effort is inherently valuable. Rather, the proposed framework separates five analytically distinct elements: contribution architecture, visibility, attribution, evaluative representation, and recognition allocation. This separation makes it possible to ask where credit may diverge from underlying contribution without assuming that either managers or technologies necessarily make erroneous judgments.

The contribution is therefore integrative and explicitly non-empirical. The framework links evidence on technological observation, human–AI judgment, algorithmic performance management, professional expertise, and work-related identity while preserving distinctions among measured performance, perceived contribution, formal evaluation, and organizational recognition. It also treats alternative explanations—including actual performance differences, employee self-presentation, task complexity, occupational norms, technological accuracy, and organizational power—as necessary constraints on interpretation. The objective is to specify a testable conceptual architecture for studying recognition in mediated work, not to claim that the proposed sequence has already been causally demonstrated.

Visibility of human effort

Visibility of human effort refers here to the extent to which consequential employee inputs become observable and interpretable to actors or systems involved in evaluation. Organizational visibility has changed as technologies have expanded observation from relatively coarse outcomes toward increasingly detailed traces of individual activity [7]. Digitally mediated work can also generate substantial digital exhaust and digital footprints that persist beyond the immediate task and can be repurposed as organizational information [8]. Yet trace abundance should not be equated with complete visibility. A system may capture clicks, outputs, response times, or transaction histories while remaining insensitive to judgment, coordination, restraint, error prevention, or contextual interpretation.

The distinction becomes especially important in knowledge-intensive work. Ethnographic evidence from the use of analytical technologies shows that workers may engage in substantial validating practices around technological outputs, including checking whether results are plausible and determining when additional scrutiny is needed [9]. Such practices may be indispensable to reliable use while remaining largely absent from the visible final product. Distributed work creates another complication: employees may themselves become responsible for demonstrating that they are present, engaged, or consequential, making the production of visibility an additional form of work rather than a neutral reflection of contribution [10].

Visibility therefore has at least two conceptually distinct forms in the proposed framework. Trace visibility concerns activity represented in observable digital records; contextual visibility concerns whether evaluators understand the expertise, coordination, discretion, and corrective activity that made an outcome possible. This distinction is proposed rather than established as a validated measurement model. It is useful because a highly traceable worker may still have poorly understood contributions, while an employee with fewer traces may perform consequential work that is visible through other organizational relationships.

Evaluative visibility can also redistribute power. Research on online sellers shows how algorithmically mediated customer evaluations can create vulnerabilities and asymmetric dependencies even when workers retain some agency in responding to them [11]. The evidence does not show that all digitally visible work is unfairly evaluated, and platform settings cannot automatically be generalized to conventional employment. More broadly, observed differences in recognition may result from real performance differences, strategic self-presentation, role design, or occupational expectations. The framework therefore treats visibility as an informational condition for attribution, not as evidence that a particular employee deserves a particular amount of credit.

Attribution between employees and technologies

Attribution concerns how observers interpret the source of an outcome. In technology-mediated work, the relevant alternatives may include predominantly human contribution, predominantly technological contribution, joint contribution, or unresolved contribution. Experimental research demonstrates that the source label attached to advice can influence how strongly people weight that advice: under some conditions, individuals exhibit greater appreciation of algorithmic than human judgment [12]. This finding establishes that technological source identity can matter to evaluation, but it does not establish how organizations distribute credit for completed work.

The perceived nature of the task also matters. Algorithm aversion varies with task characteristics, with reliance on algorithms declining when tasks are perceived as requiring more subjective judgment [13]. Delegation research further shows that human–AI collaboration depends on how tasks are partitioned and on whether decision makers possess adequate knowledge about their own capabilities relative to those of an artificial collaborator [14]. These findings suggest that attribution cannot be derived solely from technological involvement. The same technology may be understood as a calculator, delegated decision maker, collaborator, or background infrastructure depending on task architecture and the observer's assumptions.

Opacity further destabilizes attribution. Field research in professional diagnosis shows that experts develop different ways of engaging with AI when its judgments cannot be transparently reconstructed, particularly when decisions are consequential [15]. When employees must interpret, verify, reject, or contextualize opaque outputs, the resulting performance may represent an intertwined accomplishment even if organizational reporting presents the final output as technologically generated. Conversely, substantial human involvement does not establish that human judgment was decisive; human activity may be redundant, procedural, or even detrimental.

The framework therefore proposes joint contribution attribution as an analytic category for situations in which outcome production cannot reasonably be represented as exclusively human or technological. This category does not assign equal credit. It instead requires inquiry into task decomposition, delegated authority, expertise, technological opacity, intervention opportunities, and responsibility for correction. Attribution remains distinct from both visibility and performance: visible effort can be incorrectly attributed, and high performance can emerge from contributions whose relative importance remains uncertain.

Table 1 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for definitions, constructs, and conceptual boundaries for who receives credit for effort in technology-mediated organizational work?.

Table 1. Definitions, constructs, and conceptual boundaries for Who Receives Credit for Effort in Technology-Mediated Organizational Work?

Construct or Component	Definition	Problem Addressed	Evidence Basis	Distinction from Adjacent Concepts	Proposed Role	Uncertainty	Boundary Statement
Human Contribution	Cognitive, relational, coordinative, corrective, or task-based input by employees that is consequential for an outcome	Human inputs may become obscured when technologies mediate production	Established organizational and technology-mediated work literature	Contribution is not equivalent to effort expenditure, visibility, or final performance	Starting component of contribution architecture	Relative contribution may be difficult to isolate	Human involvement alone does not establish decisive contribution
Technological Contribution	Computational, informational, predictive, generative, or coordinative input supplied by a technological system	Technological involvement may be interpreted as technological authorship of an outcome	Established human–technology and algorithmic-work literature	Capability differs from authority, responsibility, and organizational credit	Parallel component of contribution architecture	Contribution depends on task design, data, configuration, and human intervention	Use of technology does not determine how credit should be allocated
Joint Contribution	Outcome production that depends materially on interdependent human and technological inputs	Binary human-versus-technology attribution can misrepresent sociotechnical production	Evidence-supported conceptual foundation; **proposed article-specific construct**	Joint contribution does not imply equal contribution	Captures nonseparable contribution structures	Relative shares may remain indeterminate	No fixed human–technology credit ratio is assumed
Effort Visibility	Degree to which consequential human activity becomes observable and	Important work may remain absent from	Established visibility and digital-work literature	Visibility is not synonymous with contribution or performance	Proposed filter between contribution	Observable activity may be incomplete or	Greater visibility does not

	interpretable to evaluators	organizational representations			and attribution	strategically produced	demonstrate greater value
Trace Visibility	Representation of activity through logs, metrics, records, or digital traces	Easily recorded activity may dominate evaluation	Established digital-work concept; **proposed subtype**	Trace availability differs from contextual understanding	Identifies what enters formal information systems	Trace completeness varies across technologies and tasks	Recorded activity cannot be treated as total effort
Contextual Visibility	Evaluator awareness of judgment, coordination, validation, restraint, and corrective work surrounding an outcome	Tacit or background contributions may remain invisible despite measurable output	**Proposed synthesis** grounded in knowledge-work research	Context concerns meaning and contribution, not activity volume	Complements trace visibility	Depends on access to situated knowledge	Contextual interpretation can itself be incomplete or biased
Attribution	Interpretation of who or what was responsible for producing an outcome	Human and technological inputs may be credited differently despite joint production	Established attribution and human–AI judgment literature	Attribution differs from objective contribution and from formal evaluation	Connects visibility to evaluative representation	Source beliefs, expertise, and task characteristics may influence judgment	Attribution cannot establish causal contribution by itself
Evaluative Representation	Organizational translation of work into scores, ratings, categories, assessments, or managerial judgments	Complex contributions may be compressed into simplified performance representations	Established performance-management literature; **proposed framework stage**	Measurement is distinct from recognition	Mediates between attribution and organizational credit	Representation validity may vary by task and system	A performance indicator is not a complete account of contribution
Credit Allocation	Assignment of acknowledgment, reward, opportunity, reputation, status, or responsibility to an interpreted contribution	Performance information must be translated into organizational recognition	**Proposed integrative construct**	Credit differs from performance measurement and causal responsibility	Final allocation stage of the framework	Formal and informal recognition may diverge	No universal rule defines the correct allocation of credit
Recognition Discrepancy	Divergence between consequential contribution and the recognition ultimately allocated to it	Contribution and recognition may fail to correspond	**Original proposed construct**	Not equivalent to dissatisfaction, low performance, or perceived unfairness	Central diagnostic concept of the framework	Requires independent evidence of both contribution and recognition	Its existence, direction, and consequences require empirical testing

Note. Constructs identified as proposed represent original conceptual elements of the Effort-Recognition Framework and should not be interpreted as empirically validated measures or causal mechanisms.

Performance measurement and credit allocation

Performance measurement concerns how organizations represent work for evaluation; credit allocation concerns what organizations subsequently do with those representations. This distinction becomes increasingly important when digital systems mediate both processes. Research on app-based work shows that algorithmic management can structure task allocation and performance-management relationships rather than merely supplying neutral information [16]. Broader work-design research identifies monitoring, goal setting, performance management, scheduling, compensation, and even termination as functions that algorithmic systems may perform or substantially influence [17]. Measurement systems therefore participate in organizational control, but their ability to structure decisions does not establish that they completely represent contribution.

The proposed framework describes evaluative representation as the intermediate layer through which work is converted into scores, ratings, categories, rankings, or managerial interpretations. This layer is necessary because organizations rarely reward raw activity directly. They evaluate selected indicators whose significance depends on the design of the job and the measurement architecture surrounding it. Research on algorithmic management emphasizes both enabling and constraining possibilities rather than a single uniform effect [18]. Consequently, the same increase in measurement precision could clarify contribution in one setting while narrowing attention to incomplete indicators in another.

Credit allocation is proposed as a separate organizational act because the same performance representation can support different recognition outcomes. A score may influence pay, promotion, task access, reputation, developmental opportunities, or managerial trust, but these consequences require interpretive and institutional choices. Even within algorithmic performance-management systems, human managers remain consequential actors whose reflexivity and behavior can shape employee trust in the broader system [19]. Technology-mediated measurement therefore does not automatically transfer responsibility for recognition decisions from managers or organizations to the technological system.

This distinction also constrains the article's normative implications. A discrepancy between recorded performance and contextual contribution may reflect deficient measurement, but it may instead reflect legitimate organizational priorities, differences in role expectations, or genuinely unequal performance. Likewise, managerial correction is not inherently superior to algorithmic evaluation because human judgment can introduce its own biases and inconsistencies. The framework therefore proposes that research examine the measurement-to-credit transition directly: which indicators become consequential, how they are interpreted, who can challenge them, and how they are translated into formal and informal recognition.

The central conceptual claim is thus narrower than an argument against technological measurement. Performance systems can provide valuable information, standardize criteria, and coordinate complex work, while still leaving unresolved questions about contribution provenance and appropriate recognition. By treating measurement and credit allocation as analytically distinct, the framework makes it possible to investigate when technologically represented performance corresponds closely to consequential effort and when it does not, without assuming either technological objectivity or human interpretive superiority.

Proposed effort-recognition framework

Recognition in mediated work is best conceptualized as a process connecting contribution to organizational judgment rather than as a direct reflection of output. Algorithm implementation can reorganize regimes of knowing through interactions between technological representations and employees' responses to them [20]. Research on machines as teammates likewise suggests that AI can occupy collaborative roles rather than functioning only as passive infrastructure [21]. These insights support a process view in which technologies help shape both production and the interpretive environment through which production is understood.

The proposed Effort-Recognition Framework begins with contribution architecture: the configuration of human, technological, and interdependent inputs involved in producing or safeguarding an outcome. Human–AI symbiosis scholarship emphasizes differentiated capabilities that may become complementary under uncertainty and complexity [22]. Hybrid-intelligence research similarly conceptualizes complex work as potentially combining human and artificial capabilities [23]. The framework does not infer equal contribution from collaboration. Instead, it asks what each actor or system contributed, which dependencies were consequential, and whether contribution can be separated without destroying the logic of joint production.

A second principle is that contribution passes through selective organizational filters. Platform research shows that algorithmic matching and control can operate together, shaping both task allocation and workers' responses [24]. The framework therefore links visibility to attribution and attribution to evaluative representation before recognition is allocated. These links are proposed rather than empirically established as a single sequence. They make explicit where contextual labor may disappear, where technological output may be over- or under-attributed, and where performance indicators may compress heterogeneous contributions into a simplified evaluative representation.

A further feature of the framework is its multilevel separation. Contribution can occur at the task or team level, visibility can be shaped by organizational information systems, attribution can reside in a manager or peer audience, and recognition can be allocated through formal policies or informal status judgments. Treating these levels as interchangeable would invite ecological and atomistic errors. The proposed sequence therefore requires researchers to specify whose contribution is being assessed, who observes it, who performs the attribution, and which organizational actor controls the eventual recognition decision. Cross-level effects remain possible, but they require evidence rather than assumption.

Figure 1 presents the original conceptual synthesis for effort-recognition framework, showing how the article's principal constructs, mechanisms, uncertainties, and decision boundaries are connected.

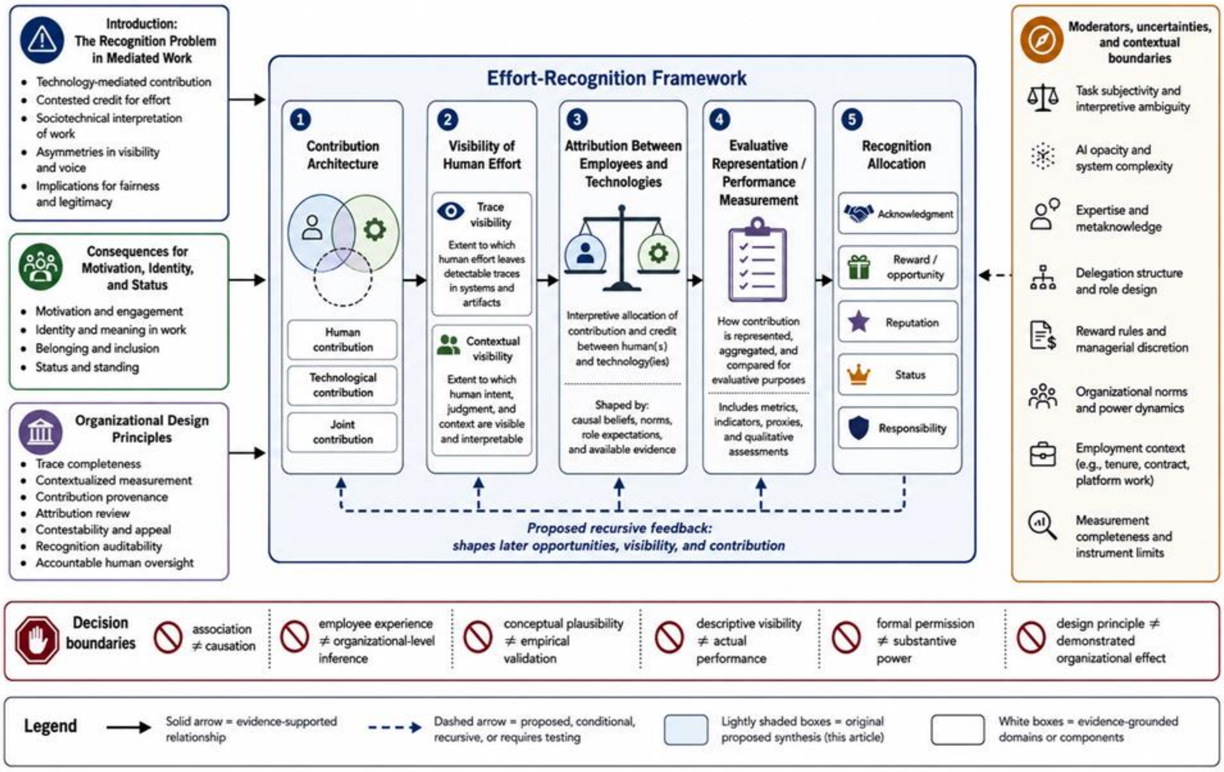

Figure 1. Effort-Recognition Framework

The proposed framework also adds a recursive path: prior recognition may affect later opportunities to contribute, become visible, receive discretion, or enter consequential assignments. That feedback is a testable proposition, not an established general effect. The proposed framework therefore treats technologically mediated contribution as a joint sociotechnical accomplishment whose recognition can depend on otherwise hidden human practices and on the architecture through which work is evaluated [3, 9, 17]. Recognition discrepancy denotes the proposed divergence between consequential contribution and the recognition eventually allocated to it; identifying such a discrepancy requires evidence about contribution independent of the recognition outcome itself.

Table 2 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for proposed mechanisms, relationships, and organizational consequences in who receives credit for effort in technology-mediated organizational work?.

Table 2. Proposed mechanisms, relationships, and organizational consequences in Who Receives Credit for Effort in Technology-Mediated Organizational Work?

Mechanism or Relationship	Antecedent	Mediator or Process	Moderator	Expected Consequence	Supporting Evidence	Rival Explanation	Validation Requirement
Selective Visibility	Technology-mediated and distributed contribution	Differential capture of traceable versus contextual work	Task observability; technological instrumentation	Contribution may become only partially represented	Established visibility and digital-work literature	Observed differences reflect genuine differences in effort	Compare digital traces with independent process-level evidence
Visibility-To-Attribution Translation	Uneven observability of human and technological inputs	Evaluators infer contribution from available information	Expertise; information access; task familiarity	More visible inputs may receive disproportionate attribution	Established attribution and visibility research; **relationship proposed**	Evaluators correctly identify the most consequential contributor	Manipulate visibility while holding actual contribution constant
Attribution Partitioning	Joint human–technology production	Assignment of responsibility across human and technological actors	Task subjectivity; AI opacity; delegation architecture	Relative credit may vary even when output is unchanged	Established human–AI judgment literature; **mechanism proposed**	Differences arise only from perceived system accuracy	Manipulate contribution source, task type, and delegation structure
Measurement Compression	Multidimensional work contribution	Reduction of heterogeneous	Indicator breadth;	Some forms of contribution may	Established algorithmic	Selected metrics	Compare evaluative

		inputs into standardized indicators	contextual information	become underrepresented	performance-management literature; **mechanism proposed**	accurately represent what the organization values	indicators with independently assessed contribution
Attribution-To-Credit Translation	Evaluative judgment about contribution	Formal or informal organizational recognition decision	Reward rules; managerial discretion; organizational norms	Similar performance representations may yield different credit allocations	**Original framework relationship**	Differences reflect legitimate organizational priorities	Link attribution judgments prospectively to actual recognition decisions
Contextual Correction	Incomplete or potentially misleading evaluative representation	Managerial or expert reinterpretation using additional context	Expertise; decision authority; quality of contextual evidence	Recognition may be revised before allocation	Evidence-supported premise; **governance mechanism proposed**	Human intervention introduces additional bias	Compare corrected and uncorrected decisions against independent criteria
Recognition Discrepancy	Mismatch across contribution, visibility, attribution, and evaluation	Accumulation of distortions across framework stages	Technology design; work structure; organizational power	Contribution and recognition may diverge	**Original proposed mechanism**	Apparent discrepancy reflects true performance differences	Independently establish contribution and recognition rather than inferring either from the other
Recognition Feedback	Prior recognition allocation	Subsequent access to assignments, discretion, visibility, or developmental opportunity	Hierarchy; labor market structure; managerial discretion	Initial recognition differences may become self-reinforcing	**Original proposed recursive relationship**	Later outcomes reflect stable differences in performance	Use longitudinal designs separating prior contribution from subsequent opportunity
Recognition Consequences	Persistent or salient recognition experiences	Interpretation of professional worth and organizational standing	Occupational identity; dependence on technology; employment context	Potential effects on motivation, identity, belonging, or status	Existing consequence literature; **credit pathway proposed**	Effects originate from job redesign, status cues, or technology use itself	Test recognition discrepancy against competing explanatory mechanisms

Note. “Expected consequence” denotes a theoretically proposed direction, not an established causal effect. Evidence bases support component phenomena; integrated pathways require direct empirical validation.

Consequences for motivation, identity, and status

Recognition matters because work is not only a production process; it is also a setting in which people construct occupational identities and infer their standing. Research on app-based work shows that depersonalizing conditions can challenge narrative identity while workers actively reconstruct accounts of who they are [25]. In another context, substitutive AI altered professional-role identity dynamics when employees encountered a system that assumed parts of their decision responsibility [26]. Neither study demonstrates that credit allocation caused these identity processes, but both show why changing the perceived locus of contribution can become personally consequential.

Status provides a related but distinct pathway. Experimental evidence indicates that people managed by algorithms can be assigned lower anticipated or perceived status, partly because observers infer less complex work [27]. The implication for the proposed framework is bounded: technological mediation may become a status cue independently of actual contribution. Thus, apparent recognition loss could reflect beliefs about task complexity, occupational prestige, or worker replaceability rather than a direct judgment about effort.

Meaningfulness and belonging also require differentiation. Evidence from crowdwork suggests that algorithmic control and algorithmic matching can have different associations with identity, belonging, and meaningfulness rather than forming a single undifferentiated exposure [28]. The framework therefore does not predict that technology-mediated recognition will uniformly diminish motivation or identity. Consequences should depend on which management function is involved, how employees interpret the allocation, and whether organizational recognition confirms or contradicts valued role identities.

This synthesis is consistent with evidence that technology-mediated work can become consequential for narrative identity, professional-role identity, and perceived status [25-27]. Recognition discrepancy is nevertheless a proposed explanatory mechanism, not a demonstrated mediator of those findings. Its strongest test would require independent measures of contribution and recognition followed over time, with competing explanations such as performance, role redesign, occupational status, and self-selection explicitly modeled.

Table 3 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for testable propositions, evaluation criteria, and practical responsibilities.

Table 3. Testable propositions, evaluation criteria, and practical responsibilities

Proposition or Criterion	Unit and Context	Observable Indicator	Evidence Required	Falsification Condition	Organizational Responsibility	Misuse Risk	Readiness Boundary
P1. Visibility Selectivity — Proposed	Employee, task, or team in digitally mediated work	Systematic difference between independently verified contribution and digitally observable activity	Matched process observations, work traces, and contribution assessments	Digital representations consistently capture consequential contribution without meaningful omission	Preserve access to relevant contextual information where consequential	Treating invisible activity as inherently valuable	Requires validated contribution and visibility measures
P2. Attribution Partitioning — Proposed	Human–AI or human–technology task	Credit allocation changes when perceived contribution source changes	Experimental or field variation in source, task, and delegation information	Attribution remains stable across source and task manipulations	Make contribution provenance interpretable where feasible	Assuming joint work warrants equal credit	Requires task-specific testing
P3. Measurement-To-Credit Slippage — Proposed	Performance-management system	Similar performance representations produce different recognition outcomes	Linked evaluation, reward, promotion, and managerial-decision data	Recognition follows validated performance indicators without systematic unexplained divergence	Document how indicators enter consequential decisions	Treating every discrepancy as measurement failure	No universal acceptable-discrepancy threshold is proposed
P4. Recognition Discrepancy — Proposed	Employee or team within an organization	Persistent divergence between independently established contribution and allocated recognition	Longitudinal, multi-source contribution and recognition measures	Independent assessment reveals no meaningful divergence	Provide a review mechanism for consequential disputes	Reframing dissatisfaction as evidence of under-recognition	Construct requires empirical validation before diagnostic use
P5. Contextual Correction — Proposed	Managerial or expert evaluation	Evaluation changes after decision-relevant contextual information is introduced	Comparative or experimental evidence of corrected versus uncorrected judgments	Contextual correction reduces validity, consistency, or fairness	Specify who may intervene and what evidence justifies adjustment	Assuming human judgment is inherently superior	Use only where added context has demonstrated informational value
P6. Contribution Provenance — Proposed Criterion	AI-supported knowledge work	Ability to reconstruct consequential human and technological inputs	Process data linking expertise, interventions, system outputs, and final decisions	Provenance information does not improve understanding of contribution	Maintain auditable records proportionate to decision importance	Excessive surveillance or inflated ownership claims	Appropriate detail depends on task risk and feasibility
P7. Contestability — Proposed Criterion	Technology-mediated evaluation or recognition decision	Availability of a reasoned challenge, review, and response process	Evidence on decision quality, perceived legitimacy, and correction rates	Contestability provides no informational or procedural benefit	Assign an accountable locus for reviewing consequential challenges	Symbolic appeal mechanisms without substantive authority	Governance hypothesis rather than universal requirement

P8. Recognition Auditability — Proposed Criterion	Organizational recognition system	Ability to trace how evidence became an evaluative and recognition decision	Decision records linking contribution information, interpretation, and outcome	Traceability fails to reveal meaningful decision logic or improve review	Maintain proportionate decision documentation	Bureaucratic burden or retrospective rationalization	Appropriate only for sufficiently consequential decisions
P9. Recognition Feedback — Proposed	Employee or team over time	Prior recognition predicts later visibility or opportunity after accounting for prior contribution	Longitudinal or multilevel data	Prior recognition has no independent relationship with later opportunity or visibility	Monitor whether recognition systems systematically concentrate developmental opportunity	Interpreting all cumulative advantage as recognition bias	Requires temporal evidence and strong alternative-explanation controls

Note. The propositions, criteria, and responsibilities are intended to make the framework falsifiable and researchable. They are not validated organizational standards, legal requirements, implementation thresholds, or evidence that any particular governance arrangement will improve organizational outcomes.

Organizational design principles

The framework implies design questions rather than universal prescriptions. First, organizations should examine whether performance representations preserve the forms of knowledge relevant to the decision being made. Field research on AI evaluation shows that apparently authoritative ground truth can omit experts' situated know-how, creating a gap between formal performance metrics and practical usefulness [29]. For recognition systems, this supports a principle of contextualized measurement: digital indicators should be treated as representations whose validity depends on what they include and exclude. Second, recognition processes should remain distinguishable from the technology that supplies evaluative information. Experimental work on human and AI decision makers in HR contexts shows differences in employees' interactional-justice perceptions [30]. Organizational capability is also relevant because effective AI use depends on combinations of resources, skills, collaboration, transparency, and governance rather than technology alone [31]. These findings do not establish a preferred recognition procedure, but they support examining who can interpret, explain, and contest technology-mediated evaluations.

Third, contribution provenance should preserve relevant human expertise. A two-year ethnography of AI development for hiring found that efforts to reduce dependence on domain experts evolved toward interdependence between machine-learning specialists and domain expertise [32]. This cautions against inferring that technological output is independent merely because the final interface makes human knowledge less visible.

Recognition-system design should therefore be treated as a contextual organizational problem involving measurement validity, employee experience of decision processes, and organizational AI capability [29-31]. The article proposes seven design principles: trace completeness, contextualized measurement, contribution provenance, attribution review, contestability, recognition auditability, and accountable human oversight. These are governance hypotheses, not validated interventions. Their relevance is conditional on task structure, employment arrangements, technological opacity, available expertise, and organizational authority. Empirical research should test whether each principle improves correspondence between consequential contribution and recognition, whether it introduces new biases or administrative burdens, and where simpler measurement systems perform equally well or better.

These principles also imply a demanding validation agenda. Researchers could combine system logs with observational records to test visibility completeness, experimentally vary source and task information to test attribution, and link performance representations to subsequent reward decisions to examine measurement-to-credit slippage. Longitudinal designs are especially important where recognition may alter later assignment opportunities or visibility. Qualitative process studies can identify forms of contribution that standardized indicators miss, while multilevel designs can separate individual perceptions from organizational allocations. A useful framework should also survive falsification: if simpler performance measures consistently explain recognition without added value from visibility, attribution, or contextual correction, the proposed architecture should be narrowed or rejected.

Conclusion

Who receives credit for technologically mediated work cannot be answered reliably by observing output, counting digital traces, or identifying whether an AI system was present. The proposed Effort-Recognition Framework separates contribution architecture, visibility, attribution, evaluative representation, and recognition allocation so that discrepancies among them become analytically visible. Its central contribution is to treat recognition as an organizational translation process rather than an automatic consequence of performance.

The framework further proposes recognition discrepancy, joint contribution attribution, and a recursive relationship between prior recognition and future visibility or opportunity. These constructs and relationships remain conceptual propositions. Existing scholarship establishes relevant mechanisms concerning observation, human–AI judgment, algorithmic management, professional expertise, identity, and status, but their integration does not constitute causal validation.
The framework is therefore most useful as a research architecture and a disciplined vocabulary for examining contested credit. Its propositions require longitudinal, experimental, qualitative, and multilevel testing across technologies and work arrangements. Future studies must independently establish contribution rather than infer it from recognition, distinguish employee perceptions from organizational allocations, and compare framework explanations with actual performance, task complexity, role design, and power. Organizational use should remain bounded by those evidential limits. The contribution offered here is not a formula for allocating credit, but a way to specify where and why the relationship between effort, technology, performance representation, and recognition requires closer empirical scrutiny.

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