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How AI Recommendations Acquire Organizational Authority through a Meta-Ethnographic Synthesis of Situated Acceptance, Professional Resistance, and Negotiated Decision Practices

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Abstract

Artificial intelligence increasingly supplies recommendations inside organizational decision processes, yet repeated use does not by itself explain when such recommendations acquire authority over professional interpretation and action. This meta-ethnographic review examines how organizational actors accept, resist, negotiate, and eventually normalize AI-mediated recommendations while retaining, redistributing, or contesting professional judgment. A reproducible search and selection process identified 24 qualitative evidence units suitable for reciprocal and refutational translation. First- and second-order constructs were translated across professional services, healthcare, public administration, policing, recruitment, finance, sales, and other organizational settings. Four interrelated interpretive domains emerged: situated acceptance, professional resistance, negotiated use, and normalization of recommendation authority. Acceptance was conditional on task compatibility, epistemic fit, intelligibility, verification possibilities, and role expectations. Resistance frequently functioned as jurisdictional, ethical, or epistemic work rather than simple technological rejection. Negotiated use involved explanation, brokerage, auditing, modification, contextual override, and selective incorporation. Normalization occurred when recommendations became recurrent reference points around which work and justification were organized, even where humans formally retained decision rights. The synthesis therefore treats organizational AI authority as relational, conditional, and reversible. AI recommendations acquire practical authority through organizational enactment rather than through technical performance, trust, or formal delegation alone.

Keywords Organizational authority, Artificial intelligence, Human–AI decision making, Professional judgment, Algorithmic recommendations, Meta-ethnography

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Introduction

Artificial intelligence is becoming embedded in organizational activities that previously depended primarily on professional interpretation, managerial judgment, and locally accumulated expertise. Contemporary organization research consequently treats AI less as an isolated technical artefact than as a development capable of altering expertise,

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coordination, role boundaries, and decision processes [1]. At the same time, theorization of AI in management remains shaped by competing assumptions about machine rationality, human agency, and the extent to which organizational actors attribute intentionality or decision competence to computational systems [2]. These disagreements matter because recommendation-producing systems enter organizations that already possess established distributions of legitimate judgment.

Earlier research on learning algorithms showed that algorithmic systems can change how expertise is constituted and how organizational knowledge is produced [3]. Work on algorithmic control similarly demonstrates that computational systems may structure behaviour while generating new forms of accommodation, contestation, and resistance [4]. Neither literature, however, makes organizational authority equivalent to technical control. Authority concerns whether a recommendation becomes a practically consequential reference for interpretation and action: an output that actors are expected to consult, explain, accommodate, justify departure from, or organize work around.

Trust is adjacent to this problem but analytically narrower. Research on human trust in AI shows that reliability, transparency, representation, and task characteristics affect whether users regard artificial systems as credible [5]. A trusted recommendation, however, need not determine organizational action, while a recommendation can acquire practical influence even among actors who remain sceptical of it. Recent qualitative synthesis in healthcare similarly shows that professional use of AI-supported decision making depends on social, organizational, and implementation conditions rather than on technical availability alone [6]. What remains insufficiently synthesized is how those situated conditions transform a recommendation from one informational input among many into an organizationally consequential reference.

This review therefore asks how qualitative studies portray the acquisition, contestation, negotiation, and normalization of authority around AI recommendations. Meta-ethnography is appropriate because the relevant evidence uses different occupational languages and theoretical vocabularies to describe overlapping processes: explaining, validating, resisting, brokering, interpreting, overriding, adapting, and incorporating algorithmic outputs. The objective is not to impose a universal developmental sequence. It is to translate these situated accounts while preserving contradictions that reveal when recommendation authority fails to emerge, remains provisional, or becomes reversible.

AI Recommendations, Professional Judgment, and Organizational Authority

The closest direct evidence treats authority as relationally accomplished. In a comparative field study of experts confronting AI decisions, Mayer and colleagues show that professionals can reconstruct their authority through the ways they explain machine-derived decisions to clients [7]. Authority therefore depends partly on whether others continue to recognize the expert as an interpretive intermediary. Leonardi and Leavell identify a related but distinct mechanism: highly detailed AI representations can create “artificial certainty,” making outputs appear more definitive than the underlying knowledge warrants and altering how stakeholders respond to experts [8]. Cruz, in turn, documents experts who actively intervene in AI-supported decisions rather than simply following recommendations, including practices of resistance and circumvention [9]. Together, these studies suggest that practical authority is negotiated through interaction with the recommendation and with those who must act on it.

Professional communities do not respond uniformly. Scarbrough and colleagues show that an identical epistemic technology can be interpreted differently by occupational actors because its meaning is filtered through role-specific understandings of expertise [10]. Faulconbridge and colleagues similarly identify intertwined boundary work through which professionals defend, adapt, or reconfigure jurisdiction when AI enters accounting and legal work [11]. In hiring, van den Broek and colleagues demonstrate that AI implementation can privilege some enactments of fairness while crowding out professional practices associated with an existing mandate [12]. Authority shifts can therefore occur through changes in what organizational practices become easier to enact, defend, or recognize as legitimate.

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Institutional and identity conditions further complicate the relationship between use and authority. Giannitsas and colleagues show that organizational actors navigate competing institutional pressures for automation and augmentation through distinct configurations of trust, distrust, evaluation, and safeguarding [13]. Ahuja and colleagues find that professionals respond to AI implementation through contesting, compromising, and connecting forms of identity work rather than through a single adaptation trajectory [14]. The broader automation–augmentation literature likewise cautions against treating substitution and complementarity as mutually exclusive organizational states [15]. An AI recommendation may therefore be frequently consulted without becoming authoritative, while selective dependence on it can coexist with active professional resistance.

The redistribution of interpretive influence can begin before routine deployment. Ethnographic research on the development of AI for hiring shows that professional expertise is translated and negotiated as system categories are constructed [16]. In predictive policing, Waardenburg and colleagues identify knowledge brokers who progressively act as messengers, interpreters, and curators between machine output and organizational users [17]. Such brokerage may increase human influence even while it makes algorithmic recommendations more actionable. In clinical diagnosis, Lebovitz and colleagues show that opacity does not produce one predictable response: professionals may engage with opaque output, attempt to contextualize it, or disengage from it [18]. Practical authority is consequently affected by who can interpret recommendations, who can question them, and whether disagreement remains institutionally viable.

Longitudinal work reinforces this processual interpretation. Grønsund and Aanestad describe human-in-the-loop configurations in which actors audit algorithmic outputs and alter the surrounding data and work arrangements [19]. Pachidi and colleagues show how symbolic conformity and advocacy around algorithmic technologies can contribute to a change in an organization's "regime of knowing," reshaping what counts as relevant knowledge and who is positioned to produce it [20]. Anthony's ethnography of analytical technologies likewise demonstrates that organizational groups differ in how extensively they validate, interrogate, or black-box computational outputs [21]. These findings imply that recommendation authority cannot be inferred from adoption alone. It is produced through repeated relations among technical outputs, professional practices, organizational expectations, and the possibility of justified departure.

Meta-Ethnographic Methodology

The review was conducted as a meta-ethnography rather than as an aggregative systematic review. Reporting followed the logic articulated in the eMERGe guidance, which treats meta-ethnography as an interpretive synthesis built through an explicit sequence of determining the intellectual interest, identifying relevant studies, reading studies, relating them, translating them, synthesizing translations, and expressing the synthesis [22]. The method was used to preserve the conceptual language and contextual boundaries of the included studies while enabling higher-order interpretation.

Defining the Intellectual Interest

The intellectual interest concerned the organizational acquisition of practical authority by AI recommendations. Methodological work on meta-ethnography emphasizes that translation requires an explicit interpretive focus rather than an unrestricted thematic aggregation [23]. Accordingly, the phenomenon of interest was defined as the process through which AI-generated recommendations become sufficiently consequential that actors orient interpretation or action around them, must justify deviation from them, or reorganize work in response to them.

This definition deliberately separated recommendation authority from technical accuracy, adoption, trust, automation, and formal decision rights. Those constructs remained eligible as conditions, neighbouring concepts, or rival explanations when qualitative evidence connected them to professional use. The review question therefore treated the article title as an empirical and interpretive problem rather than presuming that all organizational AI systems acquire authority.

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Determining Relevant Qualitative Studies

Selection followed design-appropriate guidance for meta-ethnographic synthesis, prioritizing studies rich enough to support translation of first- and second-order constructs [24]. Evidence units were eligible when they examined professional or organizational interaction with AI, machine-learning, algorithmic, or computerized recommendation systems and reported qualitative material concerning judgment, interpretation, acceptance, resistance, autonomy, expertise, implementation, use, or decision practice. Qualitative ethnographies, interview studies, field studies, comparative cases, and mixed designs with clearly separable qualitative findings were eligible. Journal quartile was not an evidence-selection criterion.

Searches were executed on 3 October 2026 through publisher-indexed scholarly sources covering organizational and information-systems outlets and major health, social-science, and interdisciplinary publishers. Supplementary searching followed titles, DOI records, reference links, and conceptually adjacent studies. Sixty-three records were identified before deduplication. Eight duplicate or version-equivalent records were removed, leaving 55 unique records for title-and-abstract screening. Twenty-two were excluded at that stage. Thirty-three reports were sought and all were retrievable for assessment. Nine were excluded after full assessment because they lacked a sufficiently direct recommendation or professional-judgment phenomenon, provided insufficient qualitative material for translation, were prospective without adequate enacted or elicited decision interaction, duplicated an underlying case without distinct constructs, or proved design-incompatible on full assessment. Twenty-four qualitative evidence units entered the meta-ethnography.

The selection logic required both topical relevance and interpretive adequacy. Consequently, conceptual papers, methodological sources, reviews, and quantitative studies could support background or later discussion but were not counted among the 24 included qualitative evidence units.

The selection process also distinguished evidence capable of contributing translatable professional practices from literature used only to define the surrounding theoretical field. **Table 1** records the resulting review logic without treating publication status or journal prestige as proxies for evidence quality.

Table 1. Selection and interpretive eligibility logic for qualitative evidence on organizational AI recommendation authority

Review operation	Executed result	Article-specific decision rule	Interpretive consequence
Records identified	63	Search concepts joined AI recommendation/decision systems with professional judgment, qualitative inquiry, organizational use, authority, autonomy, resistance, or implementation	Broad enough to capture different occupational vocabularies for recommendation authority
Duplicate/version removal	8 removed	DOI first, normalized title second	Prevented publisher or version duplication from inflating the evidence base
Title/abstract screening	55 screened; 22 excluded	Retained records had to concern professional or organizational interaction with AI-supported judgment or recommendations	Removed technically related but interpretively irrelevant AI research
Full assessment	33 assessed	Evidence had to contain qualitative material capable of yielding first- or second-order constructs	Excluded records that could not participate meaningfully in meta-ethnographic translation

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Final evidence set	24 evidence units	Qualitative constructs had to illuminate acceptance, resistance, negotiation, normalization, expertise, autonomy, brokerage, verification, or adjacent authority processes	Established the translation reservoir for reciprocal and refutational synthesis
Appraisal	All 24 retained with differing interpretive weight	Appraisal considered methodological transparency, contextual richness, traceability of interpretation, divergent cases, and direct relevance	Methodological weakness reduced interpretive confidence but did not automatically trigger exclusion
Coding preparation	Source-bound constructs retained before translation	Participant concepts and author interpretations were recorded separately where available	Reduced premature conversion of heterogeneous occupational concepts into one vocabulary

The executed evidence flow is summarized in **Figure 1**. The figure distinguishes record filtering from the more article-specific interpretive criterion: inclusion required qualitative material capable of being translated into organizational practices through which recommendations are accepted, resisted, negotiated, or made authoritative.

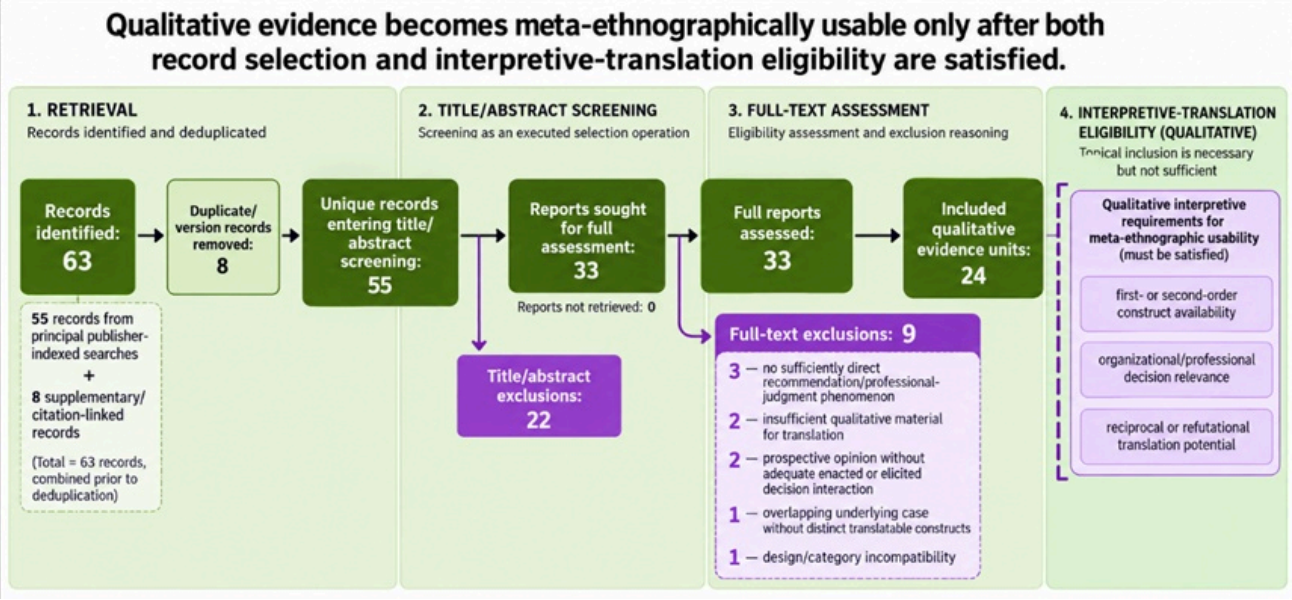

Figure 1. Qualitative evidence becomes meta-ethnographically usable only after both record selection and interpretive-translation eligibility are satisfied

Reading and Extracting First- and Second-Order Constructs

Extraction distinguished participant-level meanings from researchers' interpretations wherever the reporting permitted that distinction. Confidence considerations were informed by the qualitative evidence-synthesis principle that methodological limitations, coherence, adequacy, and relevance should be examined separately rather than collapsed into journal reputation or a single quality score [25]. Each evidence unit was read for reported practices, definitions, professional concerns, explanatory mechanisms, contradictions, applicability boundaries, and authors' stated limitations.

First-order material included professionals' reported experiences of using, questioning, explaining, resisting, or accommodating AI recommendations. Second-order constructs included concepts such as explaining practices, artificial

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certainty, algoactivism, professional boundary work, mindful evaluation, identity work, knowledge brokerage, engagement and disengagement, validation, regimes of knowing, compatibility, and trained judgment. These constructs remained linked to their original settings during extraction. They were not initially recoded into the article's four later synthesis domains because doing so would have imposed the eventual interpretation before translation.

Determining Relationships among Studies

Studies were related through their conceptual treatment of professional judgment and AI-mediated recommendations rather than through sectoral similarity alone. Some accounts were predominantly reciprocal because they described comparable processes using different terminology—for example, explanation, brokerage, verification, auditing, and contextual interpretation. Others were refutational because they reported divergent reactions to apparently similar conditions. Opacity, for instance, could provoke disengagement in one professional configuration while encouraging interrogation or compensatory checking in another. Studies were also retained as contextually distinct where apparent disagreement could plausibly arise from differences in professional jurisdiction, organizational mandate, client relations, risk environment, or implementation maturity.

This relational step prevented three forms of premature aggregation. Acceptance was not treated as equivalent to trust; professional resistance was not coded automatically as implementation failure; and continued human decision rights were not treated as proof that AI lacked practical influence.

Reciprocal Translation

Reciprocal translation identified conceptual equivalences while preserving the original occupational settings. Practices described as explanation, brokerage, contextualization, auditing, verification, or professional intervention were translated as different ways of making recommendations usable without assuming passive compliance. Likewise, role-specific sensemaking, task compatibility, epistemic fit, and verification opportunities were translated as conditions of situated acceptance.

A second reciprocal cluster concerned professional contestation. Boundary work, identity contestation, algoactivism, disagreement with machine explanations, and defence of alternative standards were conceptually related because each preserved some capacity to resist the recommendation's implied course of action. The translation therefore did not define resistance through rejection alone. Resistance could coexist with continued use and could itself reshape the terms under which AI advice became organizationally acceptable.

Refutational Translation

Refutational translation was necessary because the evidence did not support a single response trajectory. Professionals could accept AI outputs while remaining distrustful of particular features; opaque systems could provoke disengagement or more intensive interpretation; and preserved formal autonomy could coexist with perceived loss of professional or epistemic authority. Particularly important were accounts in which professionals confronted recommendations or explanations that conflicted with their own judgment. Such cases demonstrated that expertise can support either deference or rejection depending on perceived plausibility, responsibility, risk, and the surrounding organizational expectations.

The refutational reading therefore treated contradictory findings as boundaries on the synthesis. An organizational system that appears influential in one setting cannot be assumed to possess the same practical authority when professional actors retain strong interpretive resources, alternative evidence, legitimate avenues for override, or institutional support for disagreement.

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Line-of-Argument Synthesis

The reciprocal and refutational translations produced a line of argument organized around four analytically distinguishable domains: situated acceptance, professional resistance, negotiated use, and normalization of recommendation authority. These domains are not compulsory temporal stages. They identify recurring forms of relationship through which AI recommendations can become more or less consequential.

Situated acceptance concerns whether a recommendation can enter legitimate professional reasoning. Resistance concerns active efforts to contest, qualify, or defend alternative standards. Negotiated use concerns the practices through which recommendations are explained, audited, modified, contextualized, overridden, or selectively incorporated. Normalization concerns the point at which AI output becomes an expected reference around which work, justification, and organizational coordination are recurrently arranged.

Table 2 preserves the difference between reciprocal translation and refutational evidence before the four domains are reported as findings.

Table 2. Translation structure linking source-level qualitative constructs to the meta-ethnographic line of argument

Translation relation	Source-level construct family	Reciprocal meaning retained across studies	Refutational pressure retained	Resulting interpretive role
Acceptance relation	Compatibility, understandability, usefulness, epistemic fit, role-specific sensemaking, verification	AI advice becomes professionally discussable when it fits task and knowledge practices	High technical sophistication may still reduce willingness to use a system	Defines situated rather than unconditional acceptance
Jurisdiction relation	Boundary work, identity contestation, fairness mandate, algoactivism, defence of clinical reasoning	Professionals defend or renegotiate the standards by which recommendations can legitimately matter	Resistance can coexist with continued system use	Defines resistance as professional work rather than simple refusal
Translation relation	Explanation, brokerage, auditing, contextual override, validation, compromise	Human actors convert machine output into locally actionable interpretations	Brokerage may strengthen AI use while simultaneously preserving human influence	Defines negotiated use as redistribution of interpretive work
Normalization relation	Regime of knowing, recurrent reference use, routinized checking, representational certainty, embedded human–AI configuration	Repeated use can make AI output an expected organizational reference	Formal decision autonomy may persist and normalization can remain reversible	Separates practical recommendation authority from formal delegation
Cross-cutting contradiction	Opacity, responsibility, trust, risk, professional expertise	Similar constructs appear in multiple occupational settings	The same condition can support acceptance, resistance, or disengagement	Prevents a deterministic stage model

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Third-order integration	Acceptance, resistance, negotiation, normalization	Authority emerges through relations among actors, practices, and recommendations	Some settings bypass, interrupt, or reverse these relations	Supports a conditional line of argument rather than a universal sequence

Synthesis Findings

The meta-ethnographic synthesis showed that AI recommendation authority is not well represented as a binary transition from human judgment to machine control. Across the included evidence, professionals repeatedly interpreted, qualified, defended against, translated, or reorganized work around recommendations. The four domains below capture recurring configurations through which practical authority was enabled or constrained.

Situated Acceptance

Acceptance was consistently situated within an existing organization of expertise. In national-security decision environments, Weerheijm and colleagues found that system complexity, understandability, compatibility, and accountability considerations shaped how decision makers evaluated AI advisory systems [26]. More technically elaborate systems were therefore not automatically more acceptable. In a Finnish public organization developing generative-AI decision support, Choroszewicz and Rannisto show that innovation had to be justified across organizational boundaries rather than being legitimized simply through technological novelty [27].

Professional epistemic culture supplied another condition. Anichini and Kotras demonstrate that AI-generated objectivity can align with some professional standards while conflicting with others, producing different forms of epistemic tension across radiology and archaeology [28]. Lombi and Rossero similarly show why acceptance cannot be inferred from formal autonomy: radiologists could report that final clinical decisions remained theirs while simultaneously anticipating threats to professional and epistemic authority [29]. The translation across these studies indicates that situated acceptance concerns whether an AI recommendation can be incorporated into legitimate reasoning, not whether the system is merely available or technically competent.

Professional Resistance

Professional resistance appeared most clearly where recommendations conflicted with established expertise, responsibility, or legitimate alternatives. McCradden and colleagues elicited responses to AI-supported clinical scenarios in which professionals sometimes deferred to machine explanations yet in other circumstances rejected conflicting output using clinical knowledge [30]. The contradiction is analytically important because it shows that professional expertise does not predict a single orientation toward AI.

Implementation expectations likewise remained conditional. Ercia and colleagues found that clinicians and administrators assessing a machine-learning clinical decision-support system identified multiple organizational and workflow conditions that could affect whether the technology became usable in cancer care [31]. Yüksel Elgin and Elgin show that healthcare professionals negotiating AI-supported resource allocation raised questions of transparency, responsibility, and equity rather than treating computational recommendation as an ethically neutral optimization device [32]. Van Cauwenberge and colleagues document concern that computerized decision support could reduce a plurality of clinically reasonable pathways by presenting one machine-defined road as privileged [33]. Bergquist and colleagues likewise identify reliability, transparency, verification, and organizational compatibility as requirements surrounding trust in clinical AI [34].

Read together, these studies do not establish resistance as an inherently desirable or undesirable response. They show that resistance can defend alternative knowledge, jurisdiction, ethical standards, or accountability relationships. It

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therefore constitutes one way in which recommendation authority is tested before becoming embedded in practice.

Negotiated Use

Negotiated use occupied the space between simple acceptance and outright rejection. Across the synthesis, actors explained recommendations to others, translated machine output into professional categories, audited results, altered data practices, contextualized predictions, and selectively overrode proposed actions. These practices made AI usable while preventing its recommendations from operating independently of professional interpretation.

The organizational significance of such negotiation is that it redistributes expertise. A broker who repeatedly translates opaque predictions may gain influence even as the algorithm becomes more central to decision routines. A clinician who verifies recommendations may preserve professional judgment while also helping normalize the expectation that AI output should be consulted. A manager who permits selective override may simultaneously strengthen organizational reliance on the system by creating a legitimate pathway for exceptions.

Quantitative organizational evidence outside the meta-ethnographic evidence set provides a useful boundary on this interpretation. Sundaresan and Guler report that algorithmic recommendation tools can alter patterns of experiential learning in clinical work [35]. That finding is not treated as qualitative evidence of authority acquisition here, but it raises a longer-horizon question: negotiated dependence on recommendations may eventually change the very experience through which professionals acquire the capacity to contest them.

Table 3 distinguishes the mechanisms through which professional resistance and negotiated use can generate different authority consequences.

Table 3. How professional resistance and negotiated use produce different authority consequences around AI recommendations

Professional practice	Immediate relation to the AI recommendation	What remains under professional control	Potential authority consequence	Condition that prevents deterministic interpretation
Explicit rejection	Recommendation is judged implausible, unsafe, ethically problematic, or contextually inappropriate	Choice of alternative action and justification	Recommendation authority is blocked in the focal decision	Rejection may depend on unusually strong expertise or institutional permission
Jurisdictional resistance	Actors defend occupational standards or boundaries against AI-defined categories	Legitimate definition of expertise, fairness, responsibility, or acceptable reasoning	Authority remains contested even where the system continues to be used	Organizational mandates may privilege the AI-aligned practice
Explanation to clients or stakeholders	AI output is translated into an intelligible account	Framing, interpretation, contextual qualification	Expert authority can be preserved or reconstructed around machine output	Stakeholder recognition determines whether explanation succeeds
Knowledge brokerage	Specialists translate between algorithmic output and local users	Interpretation and contextualization	Practical influence may shift toward brokers	Brokerage can eventually become

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			while AI becomes more actionable	routine and less visible
Auditing and verification	Recommendation is checked before incorporation	Validation criteria and decision to accept, revise, or reject	AI gains conditional authority rather than automatic authority	Verification capacity may erode or become ceremonial
Contextual override	AI output is accepted as relevant but displaced by situational knowledge	Final interpretation and action	AI remains a reference point even when not followed	Frequent override can prevent normalization
Selective incorporation	Parts of the recommendation are combined with professional judgment	Composition of the final decision	Human and AI contributions become organizationally interdependent	Contribution boundaries may become difficult to inspect
Recurrent negotiated use	Checking, explanation, or modification becomes routine	Formal decision rights may remain human	Recommendation can become an expected default reference	Continued resistance, failed performance, or governance change can reverse the pattern

Normalization of Recommendation Authority

Normalization became analytically visible when AI output was no longer treated as an occasional external input but as a recurrent reference around which interpretation, justification, or workflow was organized. This does not mean that the system becomes an autonomous organizational actor. Recent theorization instead suggests that AI organizing capability can emerge relationally through recurring human–algorithm configurations [36]. Such a view fits the qualitative evidence: authority becomes consequential through repeated interaction among recommendations, professionals, managers, clients, technical intermediaries, and organizational rules.

Normalization also creates new governance vulnerabilities. Kellogg and colleagues show in work on generative AI that local user-focused risk practices can fail when broader system-level risks remain insufficiently addressed [37]. Applied to recommendation authority, the implication is that recurrent human involvement cannot itself be treated as evidence of effective oversight. A professional may remain formally “in the loop” while the organization increasingly treats departure from AI output as exceptional, costly, or difficult to justify.

The synthesis therefore distinguishes formal authority from practical recommendation authority. Formal decision rights may remain with professionals, managers, or public officials. Practical recommendation authority exists when AI output becomes a sufficiently established reference that organizational actors recurrently orient around it, justify deviations from it, or restructure interpretive work in response to it. The evidence further shows that normalization is reversible. Failed predictions, incompatible professional values, competing evidence, legitimate override channels, or renewed boundary work can weaken the recommendation’s practical standing.

Across the four findings subsections, the evidence therefore supports a conditional pattern rather than a universal sequence. Situated acceptance creates the possibility of legitimate use. Resistance tests the recommendation against professional, organizational, and ethical standards. Negotiated use determines how recommendation and judgment are combined. Normalization occurs only when those interactions repeatedly stabilize the recommendation as an organizational reference. None of these relations guarantees the next, and the same organization may occupy different configurations across tasks, occupational groups, or periods.

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Third-Order Interpretation of Organizational AI Authority

The translations support a third-order interpretation in which organizational AI authority is defined as the practically enacted capacity of an AI recommendation to structure interpretation and action as an expected reference point. This authority differs from formal decision rights. A physician, manager, recruiter, analyst, or public official may retain legal or organizational responsibility while nonetheless working in an environment where AI output establishes the position from which a decision begins and against which deviation must be explained.

This interpretation is relational because neither the algorithm nor the professional independently determines the authority configuration. Work on human–AI agency emphasizes that organizational agency remains distributed through arrangements linking technological capability with human interpretation and action [38]. Situated observational evidence likewise shows that AI can reorganize professional practices of seeing and judging without eliminating the professional who performs the final act of interpretation [39]. Across the included studies, authority therefore emerges through relations among recommendation production, professional interpretation, organizational expectations, clients or stakeholders, validation practices, and available avenues for disagreement.

The four synthesis domains should consequently be read as possible movements rather than mandatory stages. Acceptance can remain provisional. Resistance can redirect implementation instead of ending it. Negotiated use can stabilize into routine dependence or continue indefinitely as active checking. Normalization can weaken when poor performance, incompatible professional values, alternative evidence, governance intervention, or restored capacity for independent judgment makes deviation legitimate again. Authority acquisition is therefore reversible and context dependent.

Conceptual Model

The conceptual model separates three dimensions that organizational discussions of AI often collapse: formal decision authority, professional interpretive capacity, and practical recommendation authority. Formal authority concerns recognized decision rights and accountability. Professional interpretive capacity concerns whether actors retain the knowledge and organizational permission required to understand, question, contextualize, or reject a recommendation. Practical recommendation authority concerns how strongly organizational action is oriented around AI output in everyday work.

The dimensions can diverge. Formal authority may remain human while practical recommendation authority increases because the AI output becomes the routine starting point for judgment. Professional interpretive capacity can remain high and support productive contestation, or decline as verification becomes difficult, expertise atrophies, or organizational routines make deviation increasingly costly. Conversely, high formal authority does not ensure meaningful human control when professionals lack information, time, expertise, or legitimate opportunities to exercise independent judgment.

The synthesis identifies several recurrent conditions governing these relationships: compatibility with professional tasks, epistemic fit, inspectability, recognized expertise, explanation capacity, accountability arrangements, legitimate recourse, and organizational support for deviation. These conditions do not form an exhaustive taxonomy. They represent evidence-supported boundaries showing why similar AI capabilities can generate different authority configurations.

Discussion

The synthesis contributes to research on organizational AI by distinguishing recommendation authority from three neighbouring phenomena. First, authority is not synonymous with trust. Trust can facilitate reliance, but the included studies show that organizational actors may use systems they scrutinize or distrust because recommendations have become institutionally expected. Conversely, a trusted system may remain advisory when professional actors retain credible alternatives and unrestricted discretion [5].

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Second, authority is not equivalent to automation. The automation–augmentation distinction remains useful for describing task allocation [15], but it does not reveal whose interpretation becomes the organizational reference point. Human involvement can coexist with substantial AI authority when people mainly explain, verify, or operationalize recommendations generated elsewhere. Similarly, augmentation can preserve meaningful professional judgment when users retain the capacity to challenge assumptions and redirect action.

Third, authority cannot be inferred solely from algorithmic control. Algorithmic systems can constrain work through monitoring, evaluation, and task allocation [4], yet recommendation authority operates through a more interpretive relation. The crucial question is whether AI output becomes presumptively relevant to a decision and whether departures require explanation. This explains why apparently contradictory findings across occupations can coexist: different organizations distribute validation capacity, professional legitimacy, responsibility, and recourse differently.

The meta-ethnographic perspective also changes how resistance should be interpreted. Resistance sometimes protects jurisdiction, ethical standards, contextual knowledge, or alternative definitions of good judgment. At other times, resistance may defend established professional arrangements that themselves deserve scrutiny. The evidence therefore does not justify treating resistance as either organizational dysfunction or an inherently protective response. Its significance depends on what is being defended, who can contest whom, and whether alternative interpretations remain accountable.

Longer-term consequences require particular attention. Repeated reliance on recommendation systems may alter experiential learning [35], while emerging work on AI-enabled organizing emphasizes increasingly relational distributions of capability [36]. The present synthesis cannot establish that normalized recommendation authority necessarily erodes expertise. It does, however, identify a testable concern: when professional participation becomes primarily confirmatory, the organizational appearance of human authority may persist after the practical capacity for independent evaluation has weakened.

The boundaries separating formal rights, practical recommendation authority, and retained interpretive capacity are summarized in **Table 4.**

Table 4. Discriminating boundaries for interpreting organizational authority around AI recommendations

Observable organizational condition	What the synthesis permits researchers to infer	What remains unresolved	Discriminating implication
Professionals retain final sign-off while routinely beginning from AI output	Formal human authority and practical AI recommendation authority can coexist	Whether deviation is substantively feasible	Final decision rights alone are insufficient evidence of effective human control
Professionals routinely verify recommendations using independent expertise	AI use can coexist with retained interpretive capacity	Whether verification remains meaningful as reliance increases	Verification must be assessed as an enacted practice, not a nominal requirement
Deviation requires explanation but AI-conforming decisions do not	Recommendation authority has become organizationally asymmetric	Whether asymmetry is justified by performance or institutional convenience	Burden-of-justification patterns provide an observable marker of practical authority
Professionals modify or selectively incorporate	Authority is negotiated rather than simply	Whether negotiated use stabilizes or remains	Hybrid outcomes should not automatically be classified

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recommendations	accepted or rejected	continuously contested	as augmentation
Organizational actors cannot inspect relevant assumptions or obtain credible recourse	Formal responsibility may exceed practical decision capacity	Whether alternative institutional safeguards compensate	Accountability claims should be evaluated against usable capacities for challenge
Different professional groups respond differently to the same AI system	Authority is socially and occupationally situated	Whether differences arise from expertise, jurisdiction, incentives, or implementation design	Organization-level adoption measures can conceal divergent authority configurations
AI recommendations become routine while professional expertise remains visibly active	Normalization need not eliminate human expertise	Whether expertise remains independent or increasingly organized around AI outputs	Presence of experts is not sufficient evidence that recommendation authority remains weak
Previously normalized AI advice becomes contestable after failures, new evidence, or governance change	Recommendation authority is reversible	Which triggers produce durable reversal	Authority should be studied longitudinally rather than as a stable adoption outcome

Theoretical and Managerial Implications

Theoretically, the synthesis suggests that future research should measure AI authority through observable organizational relations rather than infer it from attitudes alone. Relevant indicators include who must explain a decision, whether deviations from AI output require justification, who can inspect the basis of a recommendation, whether alternative evidence can legitimately displace it, and which actors retain the competence and permission to do so. Trust remains important, but it cannot substitute for these authority relations.

The analysis also implies that human–AI arrangements should not be classified only by whether a person is technically present in the decision loop. Meaningful professional authority depends on usable interpretive capacity and credible recourse. An organization can formally require human review while structuring workload, information access, incentives, or accountability so that confirmation of AI output becomes the easiest defensible action. Conversely, repeated AI consultation need not amount to domination when independent expertise, verification, and justified override remain institutionally robust.

For managers, the practical implication is to examine where the burden of justification lies. A governance arrangement changes materially when accepting an AI recommendation requires little explanation but rejecting it demands extensive documentation or managerial approval. Organizations should therefore distinguish responsibility assigned on paper from the resources required to exercise judgment in practice. Monitoring should include whether professionals can access relevant contextual evidence, obtain explanations appropriate to their work, contest outputs without disproportionate penalty, and re-enter decision processes when recommendations fail.

These relationships are integrated in **Figure 2.**

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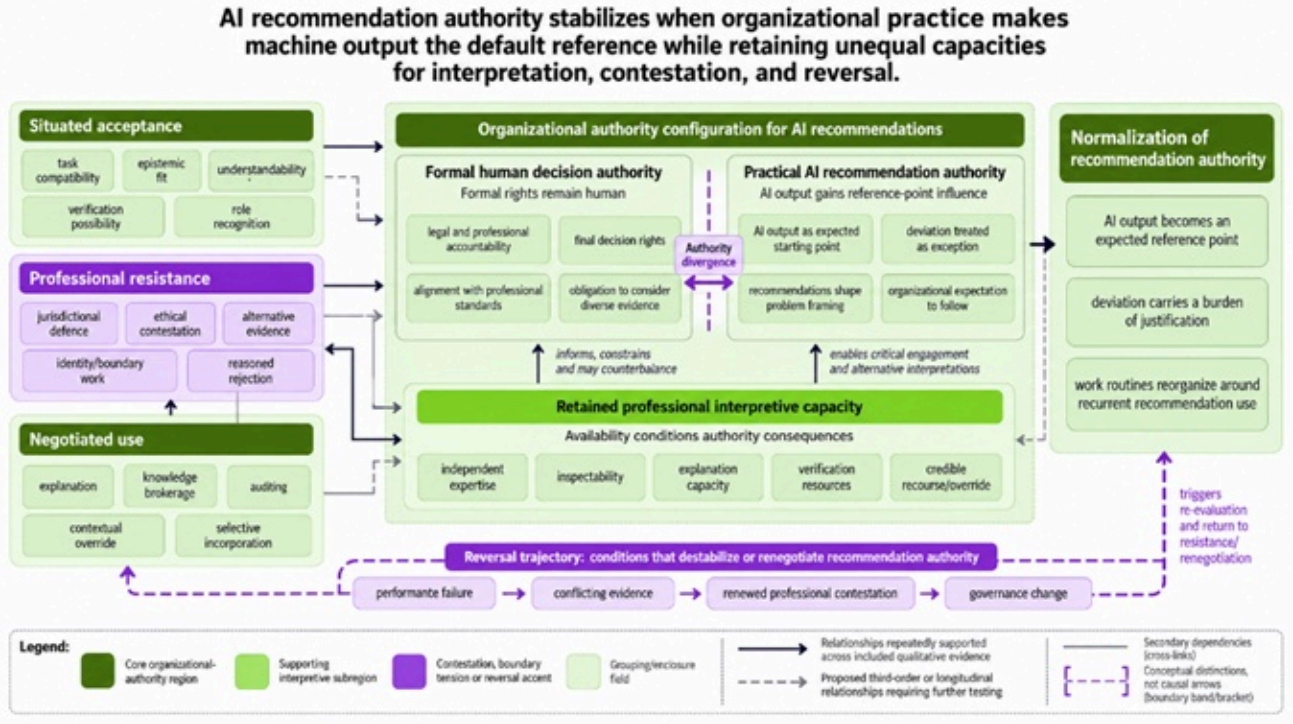

Figure 2. AI recommendation authority stabilizes when organizational practice makes machine output the default reference while retaining unequal capacities for interpretation, contestation, and reversal

Reflexivity, Limitations, and Future Research

Several limits qualify the synthesis. The search was executed through accessible publisher-indexed scholarly routes and supplementary citation-linked searching rather than through proprietary database exports. The search record is reproducible for the searches actually performed, but the review should not be interpreted as proof that every potentially relevant qualitative study indexed worldwide was captured. Meta-ethnographic guidance also recognizes that interpretive synthesis depends on the conceptual richness and reporting of included studies [22-24]. Thinly described organizational practices cannot be recovered through synthesis after the fact.

The included literature is heterogeneous in sector, implementation maturity, professional jurisdiction, and qualitative design. Some studies examine established organizational use, whereas others examine development, prospective implementation, or elicited encounters with AI-supported decisions. Findings involving simulated interaction were retained only where they produced sufficiently direct qualitative evidence and are not treated as equivalent to longitudinal observation. Confidence in the review-level interpretations therefore depends on coherence, adequacy, relevance, and methodological limitations rather than the prestige of publication venues [25].

The synthesis is also reflexive in its treatment of authority. Because “organizational AI authority” is the third-order interpretive construct produced here, it should not be retroactively attributed to study participants or authors who used different terminology. The review translates practices such as explaining, resisting, auditing, brokering, validating, or reorganizing work into an authority question while retaining their original contextual boundaries.

Future research should test the synthesis longitudinally. Particularly important questions concern whether burden-of-justification asymmetry increases over time, whether verification becomes ceremonial as reliance grows, and whether formal human authority can persist after independent professional capacity has substantially weakened. Comparative work should also examine direct organizational mandates that may bypass the acceptance–negotiation relations identified

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here, as well as cases in which normalized AI advice loses authority after visible failure or institutional intervention. Such designs would distinguish a useful interpretive synthesis from a universal causal theory.

Conclusion

AI recommendations acquire organizational authority when they become more than available information and instead function as expected reference points for professional interpretation, justification, and action. The reviewed qualitative evidence shows that this development is neither automatic nor equivalent to trust, technical accuracy, automation, or formal transfer of decision rights. It depends on situated acceptance, professional contestation, negotiated incorporation, and the organizational conditions under which recurrent use becomes normalized.

Professional judgment can remain formally authoritative while practical dependence on AI recommendations grows. Conversely, extensive AI use can coexist with substantive human authority when expertise, verification, explanation, alternative evidence, and credible recourse remain operative. The strongest conclusion is therefore conditional: organizational AI authority is enacted through social and institutional practice, remains uneven across actors and tasks, and can be resisted, reshaped, or reversed when the conditions supporting its practical authority change.

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