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The Leadership Dynamic in Algorithmic Management: Redefining Middle Management Roles in Data-Driven Cultures

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Organizational control;
Human-AI collaboration

Abstract

The diffusion of algorithmic management—software systems that assign, monitor, evaluate, and increasingly discipline labor—has moved from platform-mediated gig work into mainstream corporate settings, placing new pressure on the middle management layer that has historically mediated between strategic intent and operational execution. This paper develops a conceptual and mixed-methods research framework examining how algorithmic management reshapes middle managers' roles, authority, and legitimacy within organizations pursuing data-driven decision cultures. The research problem addressed is twofold: existing algorithmic-management scholarship has concentrated on platform and gig-economy contexts rather than salaried corporate middle managers, and existing middle-management scholarship predates the widespread delegation of monitoring, recommending, and evaluative functions to algorithmic systems. Drawing on role theory, leader-member exchange theory, and paradox theory, the paper synthesizes literature on algorithmic control mechanisms, middle-management strategic influence, data-driven organizational culture, and algorithm aversion to propose an integrative framework in which algorithmic management intensity influences middle-manager role ambiguity, which in turn shapes strategic influence and downstream employee engagement, moderated by digital leadership capability and organizational AI governance. A sequential explanatory mixed-methods design—qualitative interviews followed by a confirmatory structural survey—is proposed as the appropriate methodology, together with a formal moderated-mediation specification and a proposed measurement model. Because no primary data have yet been collected, all quantitative illustrations in this paper are explicitly labeled as proposed or illustrative rather than empirical findings. The paper contributes a theory-grounded, falsifiable framework and a reproducible research design for scholars and practitioners seeking to understand how leadership work is redefined—rather than eliminated—as organizations become more algorithmically governed, and it offers practical guidance for designing middle-management roles, training, and governance structures that preserve human judgment and employee trust under conditions of intensifying algorithmic oversight.

1. Introduction

Organizations increasingly delegate coordination, monitoring, and evaluation tasks once performed exclusively by human supervisors to algorithmic systems that ingest operational data and issue recommendations, scores, or directives. This phenomenon, first named algorithmic management in a study of ride-hailing drivers, describes "software algorithms that assume managerial functions and the institutional devices that support algorithms in practice" (Lee et al., 2015). What began as a description of platform-mediated gig work has since generalized into a broader organizational phenomenon encompassing scheduling software in retail and logistics, performance dashboards in call centers, algorithmic routing in warehousing, and AI-assisted talent and workforce analytics in corporate human resource functions. Kellogg et al. (2020) synthesize this literature into six generic mechanisms of algorithmic control—restricting, recommending, recording, rating, replacing, and rewarding—that together reconfigure how work is directed, monitored, evaluated, and rewarded, often without a human supervisor's direct involvement in each transaction. As algorithmic systems become increasingly embedded within organizational workflows, their role is consequently extending beyond operational automation toward the redistribution of managerial activities and decision rights.

At the same time, organizations are investing heavily in data-driven decision cultures, in which "authority is vested in the data quality rather than the positional power of the person with the data" (Davenport & Mittal, 2020). Building and sustaining such a culture requires executive sponsorship, data literacy, and a reallocation of decision rights away from hierarchical position toward evidentiary quality (Davenport & Harris, 2007; Kesari, 2024). The expansion of data-driven decision-making therefore does not simply introduce new technological tools; it changes the informational and organizational foundations through which managerial authority is exercised. Middle managers sit precisely at the junction where these two forces meet: they are simultaneously the human interpreters of algorithmic outputs and the organizational actors historically responsible for translating strategic intent into operational action (Floyd & Wooldridge, 1992; Wooldridge et al., 2008). Their position makes them particularly important for understanding how algorithmic management changes organizational coordination because they must interpret, contextualize, communicate, and sometimes challenge recommendations produced by increasingly autonomous systems while continuing to maintain relationships with employees and senior leadership.

The core research problem is that the growing delegation of coordination and evaluation functions to algorithmic systems is altering the substantive content of middle-management work, yet the mechanisms through which this occurs—and their consequences for managerial legitimacy, employee outcomes, and organizational performance—remain theoretically underspecified and empirically under-examined outside gig-economy settings. Industry observers report that a substantial share of organizations are actively reconsidering the size and function of their middle-management layer as algorithmic and AI-based coordination tools mature (Inspiring Workplaces, 2025), yet this shift is rarely grounded in a testable theoretical account of what middle managers do differently, and why, once algorithmic systems assume part of their coordinating role. The issue is therefore not simply whether algorithms replace particular managerial tasks, but how the redistribution of those tasks changes managerial responsibilities, discretion, strategic influence, accountability, and relationships with employees. A systematic explanation is needed to distinguish task substitution from genuine role transformation and to identify the organizational conditions under which algorithmic systems may complement rather than merely displace managerial activities.

Three interrelated gaps motivate this paper. First, the algorithmic-management literature has concentrated overwhelmingly on non-managerial, often precarious workers in platform and logistics contexts (Jarrahi et al., 2021; Lee et al., 2015; Vieira & Junte, 2025), leaving the experience of salaried middle managers—who both use and are subject to algorithmic systems—comparatively unexamined. This emphasis has generated substantial knowledge about algorithmic control over workers but provides less explanation of how algorithms alter the roles of those responsible for implementing organizational strategy and coordinating employees. Second, the middle-management literature, whose foundational typologies of strategic involvement predate large-scale workplace algorithms (Floyd & Wooldridge, 1992; Wooldridge & Floyd, 1990), has not been systematically re-theorized for a context in which synthesizing, monitoring, coordinating, and evaluative roles are partly automated. Established conceptions of middle managers as information interpreters, facilitators, and strategic contributors therefore require reconsideration when information processing and evaluation are increasingly performed by algorithmic systems. Third, the human-AI collaboration literature offers general theoretical resources—the automation-augmentation paradox (Raisch & Krakowski, 2021) and algorithm aversion (Dietvorst et al., 2015, 2018)—but these have not been sufficiently integrated into a management-specific framework that connects algorithmic system design, managerial role redefinition, and organizational outcomes within a single testable model. The resulting theoretical gap concerns not only technology adoption but also the changing distribution of managerial authority and the behavioral consequences of that redistribution.

Understanding this dynamic matters academically because it tests whether long-standing middle-management role typologies remain valid under conditions of algorithmic mediation and extends control theory and paradox theory into an under-theorized organizational layer. It also provides an opportunity to connect research traditions that have generally developed in parallel: algorithmic management explains how software can perform managerial functions, middle-management research explains how managers translate strategy and coordinate organizational activity, and human-AI collaboration research explains how individuals interact with automated recommendations and decision systems. Bringing these perspectives together can clarify whether algorithmic systems primarily substitute for established managerial activities, augment existing roles, or generate qualitatively different forms of managerial work. It matters practically because middle managers disproportionately shape frontline employee engagement, retention, and change implementation (Balogun, 2003; Huy, 2001). If algorithmic systems erode middle managers' perceived legitimacy or increase role ambiguity without corresponding investment in digital leadership capability, organizations risk undermining the very human capacities—sensemaking, trust-building, contextual judgment, and relational coordination—that make data-driven strategies executable in practice. Conversely, appropriately governed algorithmic systems may allow managers to redirect attention from routine monitoring toward higher-order interpretation, employee development, strategic coordination, and exception management.

Against this background, the study pursues five objectives. First, it synthesizes and critically integrates the algorithmic-management, middle-management, and human-AI collaboration literatures into a unified conceptual framework. Second, it theorizes the mechanisms through which algorithmic management intensity influences middle-manager role ambiguity, strategic influence, and downstream employee engagement. Third, it specifies the moderating roles of digital leadership capability and organizational AI governance in shaping these relationships. Fourth, it designs a rigorous and reproducible mixed-methods research protocol, including a measurement strategy and formal statistical model, capable of empirically testing the proposed framework. Fifth, it derives practical implications for organizational design, managerial training, and algorithmic governance. Collectively, these objectives position algorithmic management not merely as a technological intervention but as an organizational transformation mechanism that can alter managerial roles, authority structures, and employee-facing processes.

The paper makes several contributions to the literature. First, it develops a theory-grounded conceptual framework that extends middle-management role theory into algorithmically governed organizations, thereby connecting managerial role transformation with the increasing delegation of organizational functions to algorithms. Second, it develops a formal, falsifiable moderated-mediation model with explicit hypotheses (H1–H5) suitable for empirical estimation and designed to clarify the pathways through which algorithmic management intensity may influence managerial and employee outcomes. Third, it develops a literature-grounded typology linking Kellogg et al.'s (2020) six mechanisms of algorithmic control to specific middle-manager role transformations, thereby extending the application of algorithmic-control mechanisms beyond their dominant focus on frontline workers. Fourth, it provides a reproducible sequential explanatory mixed-methods protocol, including measurement strategy, sampling approach, and validity safeguards, to support systematic empirical investigation of the proposed relationships. Fifth, it develops practically oriented governance and leadership-development recommendations for organizations implementing algorithmic management, with particular attention to preserving managerial accountability, contextual judgment, and appropriate human oversight as algorithmic decision support becomes more deeply embedded in organizational processes.

The remainder of the paper is organized as follows. Section 2 critically reviews the relevant literature and presents a comparative synthesis table. Section 3 develops the theoretical and conceptual framework, including the study's constructs and conceptual diagrams. Section 4 formalizes the research hypotheses. Section 5 details the proposed mixed-methods methodology and data sources. Section 6 presents the mathematical and statistical model specification. Section 7 outlines the proposed evaluation framework and illustrative, non-empirical results. Sections 8 through 11 discuss interpretation, explainability considerations, ethics and governance, and robustness and validity. Sections 12 through 14 address limitations, future research, and conclusions, followed by the reference list.

2. Literature Review

This review is organized thematically around four literatures that must be integrated to theorize the present research problem: algorithmic management and its control mechanisms; middle-management roles and strategic influence; data-driven organizational culture; and human-algorithm collaboration and trust. Rather than summarizing studies chronologically, each subsection critically compares perspectives, identifies points of convergence and disagreement, and isolates what remains unresolved.

2.1 Algorithmic Management: Origins and Mechanisms

The term algorithmic management originates in a qualitative study of Uber and Lyft drivers, which found that ride-hailing platforms assigned, optimized, and evaluated work through software and tracked data in ways that replicated core managerial functions—work assignment, informational support, and performance evaluation—without a human manager directly performing them (Lee et al., 2015). Kellogg et al. (2020) extend this foundational work into a general theory of algorithmic control, arguing that algorithms restrict workers' choice sets, recommend courses of action, record behavioral data, rate performance, replace underperforming workers, and reward compliance. Framing algorithmic control through Edwards's (1979) contested-terrain perspective, Kellogg et al. (2020) emphasize that algorithmic technologies do not eliminate managerial power struggles but relocate and intensify them: control becomes more granular, more continuous, and less visible to those being managed.

Jarrahi et al. (2021) extend this analysis specifically to managers rather than frontline workers, observing that algorithmic management "can also decrease the power and agency of individual managers" even as it increases the control capacity of management as a collective function. They describe a spectrum of human-algorithm arrangements ranging from full delegation to sequential and aggregated decision-making, in which managers retain varying degrees of discretion over whether and how to act on algorithmic recommendations. This managerial-agency angle is critical to the present paper's problem: algorithmic management is not merely something middle managers administer to others, but something that is increasingly administered to them.

Empirical evidence from adjacent sectors reinforces this picture. In a qualitative study of the Spanish dark-stores (rapid grocery delivery) sector, Vieira and Junte (2025) find that algorithmic management reshapes workplace social relations differently depending on whether technology is deployed primarily for surveillance and coercion or in service of normative, relationally embedded forms of control, with middle managers occupying an ambiguous position between enforcing algorithmic directives and preserving legitimacy with frontline staff. This finding is consequential for the present framework because it suggests that the effect of algorithmic management on managerial role clarity and legitimacy is not fixed but contingent on system design and managerial practice—precisely the contingency this paper's framework seeks to formalize.

2.2 Middle-Management Roles and Strategic Influence

Long before algorithmic management became salient, strategy-process scholarship established that middle managers are not passive conduits of top-management decisions but active shapers of strategy. Floyd and Wooldridge's (1992) influential typology identifies four roles—championing alternatives, synthesizing information, facilitating adaptability, and implementing deliberate strategy—organized along behavioral (upward/downward) and cognitive (integrative/divergent) dimensions. Wooldridge and Floyd (1990) show that middle-management involvement in strategy affects organizational performance primarily by improving the quality of strategic decisions rather than merely the efficiency of implementation, a finding that complicates any view of middle managers as purely executional. A later synthesis (Wooldridge et al., 2008) consolidates twenty-five years of this research, concluding that middle managers' synthesizing and championing roles—both of which depend on interpretive judgment and informal influence—are as consequential to organizational outcomes as their formal implementation role.

Complementing this strategy-process tradition, Huy (2001) documents middle managers' distinctive capacity for emotional balancing and change facilitation, arguing that their intermediate structural position gives them unique access to both strategic intent and frontline sentiment. Balogun (2003) similarly reframes middle managers as change intermediaries whose sensemaking activity—rather than simple compliance—determines how organizational change is enacted. Both perspectives converge on the claim that middle managers' value lies substantially in judgment-intensive, relationally embedded work: precisely the kind of work that algorithmic recording, rating, and recommending mechanisms are now beginning to partially automate or supervise. This creates the theoretical tension this paper investigates: if algorithmic systems assume the informational and evaluative substrate of synthesizing and championing roles, do middle managers lose strategic influence, or does their role migrate toward interpretation and legitimation of algorithmic outputs?

2.3 Data-Driven Organizational Culture and Decision Authority

A parallel literature examines what it takes for organizations to become genuinely data-driven. Davenport and Harris (2007) argue that competing on analytics requires embedding analytical capability into core business processes and, crucially, into how decisions are authorized—not merely into reporting infrastructure. Davenport and Mittal (2020) sharpen this point, contending that data-driven cultures redistribute decision authority away from hierarchical position and toward evidentiary quality, and that this redistribution must be actively led by senior executives rather than assumed to emerge from technology adoption alone. Kesari (2024) adds that data literacy and cross-functional "data ambassador" roles are necessary to translate analytical capability into shared organizational language—a translation function structurally similar to the synthesizing role Floyd and Wooldridge (1992) attribute to middle managers.

The tension this literature introduces for the present study is that data-driven cultures explicitly seek to de-emphasize positional authority in favor of data quality, while classical middle-management theory grounds managerial influence precisely in structural position and interpretive access. Reconciling these two logics is one of the unresolved problems this paper's framework addresses: middle managers in data-driven cultures may retain influence not by controlling information flow, as in classical hierarchies, but by curating, contextualizing, and legitimating algorithmic outputs for both subordinates and superiors.

2.4 Human-Algorithm Collaboration, Automation, and Trust

Raisch and Krakowski (2021) offer a paradox-theoretic account of AI in management, arguing that automation (machines replacing human tasks) and augmentation (machines and humans collaborating) are not a simple either/or choice but interdependent, persistently tense organizational conditions. Their analysis implies that organizations which pursue automation of managerial coordination tasks without corresponding augmentation of managerial capability risk reinforcing cycles of value erosion, whereas organizations that treat automation and augmentation as complementary can achieve capabilities neither could deliver alone. This paradox lens is directly applicable to middle management: algorithmic systems can automate scheduling, monitoring, and first-pass evaluation (reducing certain managerial tasks) while simultaneously augmenting managers' situational awareness (expanding their informational reach), and the net effect on role clarity and influence depends on how organizations balance the two. A second strand concerns whether managers actually trust and use algorithmic recommendations once available. Dietvorst et al. (2015) demonstrate experimentally that people lose confidence in algorithmic forecasters more quickly than in human forecasters after observing identical errors—a phenomenon they term algorithm aversion—even when the algorithm outperforms the human on average. In follow-up work, Dietvorst et al. (2018) show that allowing users even minimal control over an imperfect algorithm's outputs substantially increases their willingness to rely on it, suggesting that perceived autonomy, not algorithmic accuracy alone, governs adoption. For middle managers who must both use algorithmic systems and answer for their outputs to subordinates, this literature suggests that trust calibration is not automatic and is a plausible mechanism linking algorithmic system design to managerial role strain. These findings indicate that managerial responses to algorithmic systems may depend not only on system performance but also on the degree of control managers retain over algorithmic outputs. Greater opportunities to review, modify, or contextualize recommendations may increase managers' willingness to incorporate algorithmic guidance into their existing decision processes. Conversely, highly prescriptive systems may create tensions when managerial judgment is constrained despite managers retaining responsibility for outcomes. This tension is particularly relevant when algorithmic recommendations conflict with managers' experiential knowledge or contextual understanding of employees and tasks. The resulting discrepancy between formal decision authority and practical discretion may contribute to role ambiguity and perceived responsibility without equivalent control. Trust calibration may therefore operate as an important mechanism through which algorithmic management influences the distribution of managerial influence. Managers may also develop different patterns of reliance depending on task complexity, perceived system transparency, and the consequences associated with erroneous recommendations. Accordingly, examining algorithmic management requires attention to both the technical characteristics of decision-support systems and the organizational conditions under which managers interpret, accept, modify, or reject algorithmic recommendations. These dynamics also suggest that algorithmic systems can reshape managerial discretion without eliminating formal accountability for decisions. The extent to which managers can contextualize algorithmic recommendations may therefore influence how responsibility is experienced within digitally mediated work structures. Differences in system transparency may further affect whether managers perceive algorithmic outputs as complementary resources or constraints on professional judgment. Such perceptions can shape patterns of selective reliance, particularly when algorithmic recommendations are applied to complex or ambiguous managerial situations. Consequently, the organizational consequences of algorithmic management should be examined through both changes in decision processes and changes in the managerial roles surrounding those processes.

2.5 Synthesis and Research Gap

Table 1 compares the studies reviewed above across method, context, key findings, and limitations, and situates the specific gap each leaves open. Taken together, the literature establishes that (a) algorithmic control operates through identifiable, recurring mechanisms (Kellogg et al., 2020); (b) middle managers' strategic value has historically rested on judgment-intensive synthesizing and championing activity (Floyd & Wooldridge, 1992; Wooldridge et al., 2008); (c) data-driven cultures seek to relocate decision authority toward evidentiary quality (Davenport & Harris, 2007); and (d) the net organizational effect of algorithmic delegation depends on a paradoxical balance between automation and augmentation, further complicated by predictable patterns of algorithm aversion (Dietvorst et al., 2015; Raisch & Krakowski, 2021). No existing study, however, integrates these four literatures into a single framework that specifies how algorithmic management intensity propagates through middle-manager role ambiguity to influence strategic influence and employee outcomes, nor formalizes the moderating conditions—digital leadership capability and AI governance—under which this propagation is attenuated or amplified. This is the gap the present paper addresses. This integrated framework enables the relationships among algorithmic control, managerial roles, and organizational outcomes to be examined within a common analytical structure. It also provides a basis for investigating how managerial capabilities and governance arrangements shape responses to increasing algorithmic delegation. By connecting these dimensions, the framework extends existing discussions beyond isolated effects of automation or managerial adaptation. The proposed model therefore establishes a foundation for empirically testing the organizational and behavioral consequences of algorithmically mediated authority.

Table 1: Literature Comparison: Algorithmic Management, Middle Management, and Data-Driven Culture

Study	Year	Method	Context	Key Finding	Limitation / Gap
Lee, Kusbit, Metsky, & Dabbish	2015	Qualitative interviews + archival analysis	Uber/Lyft drivers	Coined “algorithmic management”; algorithms perform assignment, informational, and evaluative functions	Limited to platform gig work; no managerial-layer perspective
Kellogg, Valentine, & Christin	2020	Conceptual review/synthesis	Cross-industry	Identifies six mechanisms of algorithmic control (restrict, recommend, record, rate, replace, reward)	Mechanisms not linked to middle-manager role content specifically
Jarrahi, Newlands, Lee, Wolf, Kinder, & Sutherland	2021	Conceptual review	Cross-industry	Algorithmic management can reduce individual managers' power even as collective management control rises	Does not formalize testable relationships or moderators
Vieira & Junte	2025	Qualitative (51 interviews)	Spanish dark-stores (rapid grocery delivery)	Effects on workplace relations vary by whether algorithms are used coercively or relationally	Sector-specific; does not isolate middle-manager strategic influence
Floyd & Wooldridge	1992	Survey (259 managers, 25 firms)	Diverse corporate settings	Middle managers exercise four distinct strategic roles varying by direction and cognitive orientation	Predates algorithmic/AI-mediated coordination systems
Wooldridge & Floyd	1990	Survey	Corporate strategy process	Middle-management involvement improves decision quality more than implementation efficiency	Same historical limitation; no technology dimension
Wooldridge, Schmid, & Floyd	2008	Literature synthesis	Strategy-process research, 25-year span	Synthesizing and championing roles are as consequential as implementation	Calls for updated theorizing but does not address algorithmic context
Davenport & Harris	2007	Practitioner-oriented synthesis/case analysis	Corporate analytics adopters	Competing on analytics requires embedding decision authority in data quality, not position	Limited empirical generalizability; not peer-reviewed academic study
Raisch & Krakowski	2021	Conceptual / paradox-theory review	Cross-industry AI adoption	Automation and augmentation are interdependent, paradoxical, not a simple trade-off	Framework not empirically tested; management-level only
Dietvorst, Simmons, & Massey	2015	Experimental (5 studies)	Forecasting tasks	People lose trust in algorithms faster than in humans after observing errors (“algorithm aversion”)	Laboratory tasks; not tested in live managerial-authority context
Dietvorst, Simmons, & Massey	2018	Experimental	Forecasting tasks	Allowing users to adjust algorithmic output increases reliance on imperfect algorithms	Same context limitation as above

3. Theoretical and Conceptual Framework

3.1 Theoretical Foundations

The framework draws on three complementary theoretical traditions. First, role theory—and specifically the concept of role ambiguity, the degree to which the expectations, methods, and consequences of a job role are unclear to the role occupant—provides the mechanism through which algorithmic delegation is expected to affect middle managers psychologically before it affects their behavior or influence. Second, leader-member exchange (LMX) theory (Graen & Uhl-Bien, 1995) supplies the relational lens through which perceived legitimacy of authority is theorized: LMX theory holds that leaders' influence depends on the quality of dyadic exchange relationships rather than formal position alone, which is consistent with the expectation that middle managers retain influence in algorithmically governed settings chiefly through relational and interpretive work rather than positional control. Third, paradox theory, as applied to management and AI by Raisch and Krakowski (2021), frames automation and augmentation as persistent, interdependent tensions rather than a single linear continuum, which justifies modeling algorithmic management intensity as having potentially divergent direct and indirect effects on managerial influence (see Section 4). These traditions are supplemented by Edwards's (1979) contested-terrain perspective on organizational control, which underlies Kellogg et al.'s (2020) six mechanisms, and by upper-echelons reasoning (Hambrick & Mason, 1984), which supports the inclusion of individual manager characteristics (e.g., digital self-efficacy) as boundary conditions on how algorithmic systems are experienced and acted upon. Together, these perspectives provide an integrated theoretical foundation for examining.

3.2 Key Constructs

i. Algorithmic Management Intensity (AMII): the extent to which task assignment, monitoring, and evaluation of a middle manager's unit are mediated by algorithmic systems, operationalized across the six mechanisms identified by Kellogg et al. (2020).

ii. Role Ambiguity (RA): the degree of uncertainty a middle manager experiences regarding the scope, expectations, and evaluative criteria of their role following algorithmic delegation.

iii. Digital Leadership Capability (DLC): a manager's demonstrated ability to interpret, contextualize, and communicate algorithmically generated information to subordinates and superiors.

iv. AI Governance and Transparency (GOV): the presence of organizational policies, explainability practices, and oversight mechanisms governing how algorithmic systems are designed, audited, and appealed.

v. Middle-Manager Strategic Influence (MMSI): the extent to which a middle manager continues to shape strategic decisions through championing, synthesizing, facilitating, and implementing activity (Floyd & Wooldridge, 1992).

vi. Employee Work Engagement (EWE): frontline employees' vigor, dedication, and absorption in their work, treated here as a downstream organizational outcome of managerial role clarity and influence.

3.3 Proposed Conceptual Framework

Figure 1 presents the overall conceptual framework. Organizational context, algorithmic system characteristics, and individual manager characteristics jointly shape how middle-manager roles are redefined under algorithmic management—moving, in the framework's central proposition, along four parallel transitions: from controller to interpreter, from supervisor to sense-maker, from gatekeeper to boundary-spanner, and from evaluator to context-provider.

This redefinition operates through three mediating psychological and relational states—trust calibration in algorithmic advice, role ambiguity, and perceived legitimacy of authority—which jointly determine downstream outcomes. Organizational AI governance is modeled as a cross-cutting moderator of the mediating pathways, and outcomes are permitted to feed back into algorithmic system design and managerial capability investment over time, consistent with the cyclical, non-static character of paradoxical tensions described by Raisch and Krakowski (2021).

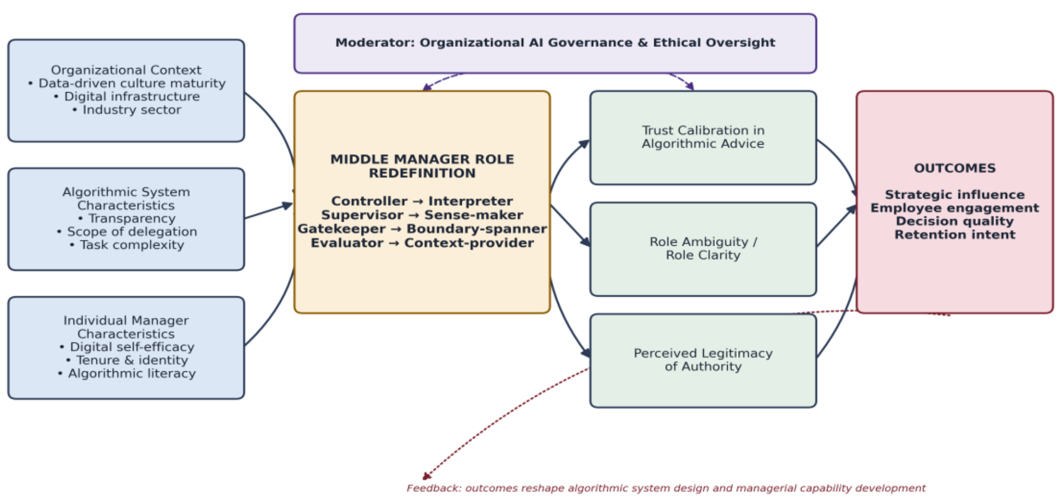

Figure 1: Proposed conceptual framework linking algorithmic management antecedents, middle-manager role redefinition, mediating mechanisms, and organizational outcomes.

Figure 1 details the mechanism-level logic underlying the central role-redefinition construct, mapping each of Kellogg et al.'s (2020) six mechanisms of algorithmic control onto a specific, theorized change in middle-manager role content. This mapping is a theoretical contribution of the present paper: whereas Kellogg et al. (2020) develop these mechanisms primarily with respect to frontline and platform workers, this paper extends the typology to the managerial layer itself. This extension reframes algorithmic control as a phenomenon that can reshape not only task execution but also the distribution and composition of managerial responsibilities. Each mechanism is therefore interpreted in terms of how algorithmic systems may alter managerial discretion, monitoring practices, decision authority, and coordination activities. The framework highlights that middle managers may increasingly operate as intermediaries between algorithmic recommendations, organizational objectives, and employee-level implementation. Such a shift can transform traditional managerial functions from direct supervision toward algorithm-mediated coordination, interpretation, and exception handling. The mapping also emphasizes that the effects of algorithmic control are likely to vary according to the specific mechanism through which control is exercised. By connecting established algorithmic-control mechanisms to changes in managerial role content, Figure 3 provides a structured basis for examining the organizational consequences of increasing algorithmic mediation. This mechanism-level perspective consequently supports future empirical investigation of how algorithmic control redistributes managerial discretion, accountability, and decision-making authority within digitally transformed organizations. This integrated perspective further clarifies how algorithmic control may simultaneously reshape managerial responsibilities, interpersonal relationships, and organizational decision structures. This perspective further recognizes that algorithmic control can redistribute not only operational tasks but also the interpretive responsibilities through which managers exercise influence. Accordingly, the framework considers managerial adaptation as a multidimensional process involving role expectations, relational exchanges, and evolving control structures. These theoretical linkages provide a coherent basis for examining variations in managerial responses to algorithmically mediated work environments.

They also support the identification of boundary conditions under which algorithmic delegation may alter rather than eliminate the strategic contribution of middle managers. This redistribution may also influence how managers prioritize competing organizational demands and allocate attention across routine and exceptional tasks. The resulting changes in role content can affect both the perceived scope of managerial responsibility and the processes through which influence is exercised. Consequently, the framework provides a basis for examining how algorithmic mediation may produce new forms of managerial coordination and accountability. These changes may further redefine the boundary between managerial judgment and algorithmic authority within organizational decision processes. Managers may consequently devote greater attention to interpreting system outputs, resolving exceptions, and communicating algorithmically informed decisions to employees. The redistribution of these activities can create new coordination requirements between managerial expertise, system-generated information, and organizational governance mechanisms. It may also alter the relational dimension of management by changing how managers explain decisions, negotiate constraints, and maintain employee engagement. Taken together, these mechanisms position algorithmic mediation as a potential source of structural and relational change in the evolving role of middle managers.

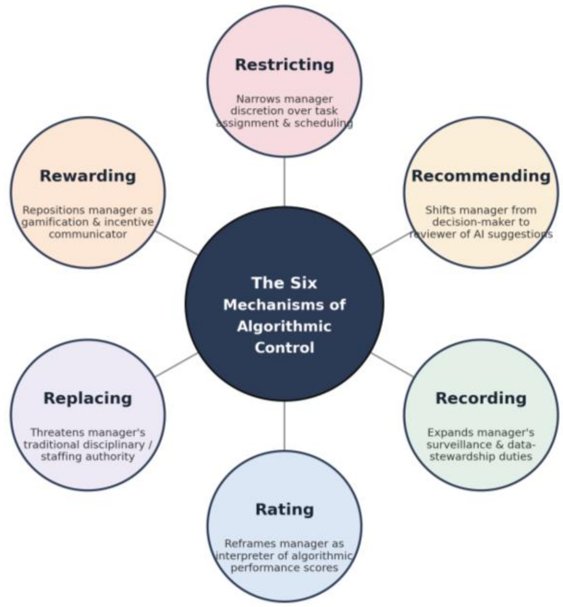

Figure 2: The six mechanisms of algorithmic control (adapted from Kellogg et al., 2020) and their theorized effects on middle-manager role content.

4. Research Hypotheses

Building on the conceptual framework, the paper advances five formal hypotheses, illustrated as a proposed structural model in Figure 4. These hypotheses translate the research questions in Section 1.6 into directional, empirically testable relationships among the constructs defined in Section 3.2. Together, these relationships establish a coherent analytical structure for examining the proposed effects of algorithmic management on managerial and organizational outcomes.

H1. Algorithmic management intensity and role ambiguity.

Higher algorithmic management intensity (AMII) is positively associated with middle managers' role ambiguity (RA), because the delegation of coordination and evaluative functions to algorithmic systems removes previously self-evident cues about what the manager's own judgment is expected to contribute.

H2. Role ambiguity and strategic influence.

Role ambiguity (RA) is negatively associated with middle-manager strategic influence (MMSI), because uncertainty about role expectations reduces managers' willingness and perceived legitimacy to champion alternatives or synthesize information upward.

H3. Governance and role ambiguity.

Organizational AI governance and transparency (GOV) is negatively associated with role ambiguity (RA), such that clearer explainability practices and appeal mechanisms reduce the uncertainty introduced by algorithmic delegation, independent of algorithmic management intensity.

H4. Strategic influence and employee engagement.

Middle-manager strategic influence (MMSI) is positively associated with frontline employee work engagement (EWE), consistent with prior evidence that middle managers' facilitating and sense-giving activity shapes how employees experience organizational change and direction (Balogun, 2003; Huy, 2001).

H5. Moderating role of digital leadership capability.

Digital leadership capability (DLC) moderates (buffers) the negative relationship between role ambiguity and strategic influence (H2), such that the negative effect of role ambiguity on strategic influence is weaker among managers with higher digital leadership capability.

An additional, exploratory direct path from algorithmic management intensity to strategic influence (H1', depicted as a non-significant direct effect in Figure 4) is included to test whether the relationship is fully or only partially mediated by role ambiguity, consistent with the paradoxical, non-linear character of automation-augmentation tensions (Raisch & Krakowski, 2021).

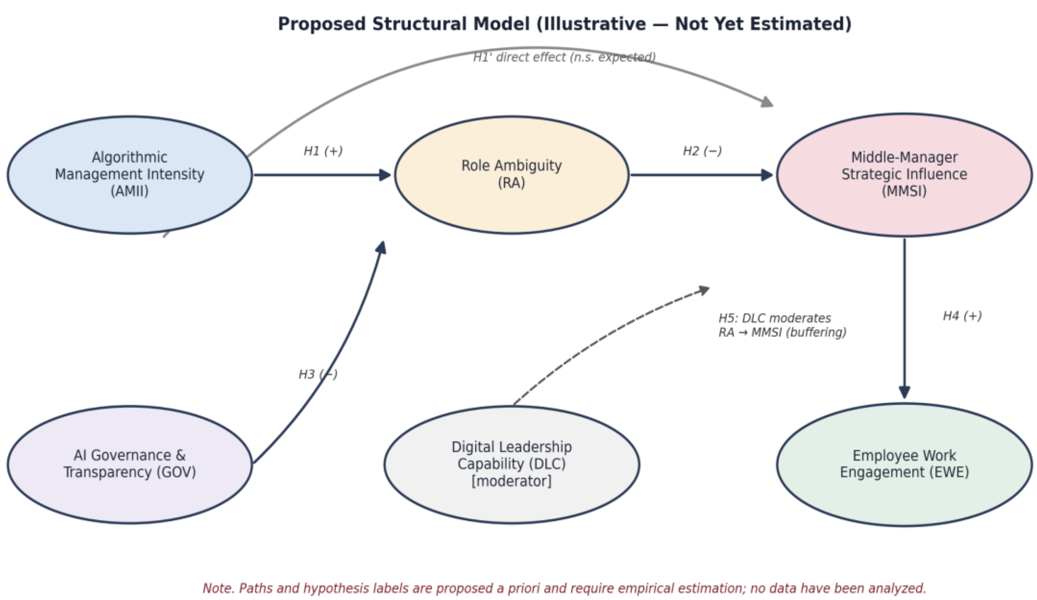

Figure 3: Proposed structural model with formal hypotheses (H1–H5). This model is theoretical and has not yet been estimated; all paths require empirical testing.

5. Proposed Methodology

No primary data have been collected for this paper. This section specifies a rigorous, reproducible research design capable of testing the framework and hypotheses developed in Sections 3 and 4. All sample sizes, instruments, and procedures below are proposed specifications for future data collection, not descriptions of completed research.

5.1 Research Design

A sequential explanatory mixed-methods design is proposed (Figure 2). Phase 1 is qualitative and exploratory: semi-structured interviews with middle managers are used to ground the constructs in lived experience, refine survey items, and validate the applicability of Kellogg et al.'s (2020) six-mechanism coding scheme to managerial (rather than only frontline) roles. Phase 2 is quantitative and confirmatory: a cross-sectional survey of middle managers is used to estimate the structural model specified in Section 4 via structural equation modeling (SEM). Phase 3 integrates findings from both phases through triangulation and member-checking. This design is appropriate because the research questions require both inductive theory refinement (given the framework's novelty) and deductive hypothesis testing (given the formal moderated-mediation model already specified).

The qualitative phase is expected to identify context-specific manifestations of algorithmic control that may not be adequately captured by predetermined survey measures. Insights from participant accounts can therefore inform item refinement by clarifying terminology, behavioral indicators, and dimensions of managerial role change. The coding process should use Kellogg et al.'s (2020) framework as an initial analytical structure while allowing emergent themes to be incorporated where theoretically justified. Findings from Phase 1 will subsequently inform the operationalization of constructs and improve the contextual relevance of the quantitative measurement model. Phase 2 will then provide a systematic assessment of the hypothesized relationships among algorithmic control, role redefinition, and the proposed moderating and mediating mechanisms. The integration stage will compare qualitative themes with quantitative patterns to identify areas of convergence, complementarity, or potential theoretical inconsistency. Member-checking will further enhance interpretive credibility by allowing selected participants to assess whether the synthesized findings reasonably reflect their reported workplace experiences. Taken together, the sequential design provides a methodological bridge between exploratory theory development and confirmatory empirical testing, thereby strengthening the study's overall theoretical and methodological rigor. The sequential structure also enables methodological findings from the qualitative phase to guide the specification and interpretation of the subsequent quantitative analysis. Cross-phase comparison can reveal whether theoretically anticipated mechanisms are consistently reflected in managers' reported experiences and measured construct relationships. Discrepancies between qualitative and quantitative findings can be examined as theoretically meaningful evidence rather than treated solely as methodological inconsistencies. This integrated approach ultimately strengthens the credibility of the proposed framework by linking contextual evidence with systematic statistical assessment.

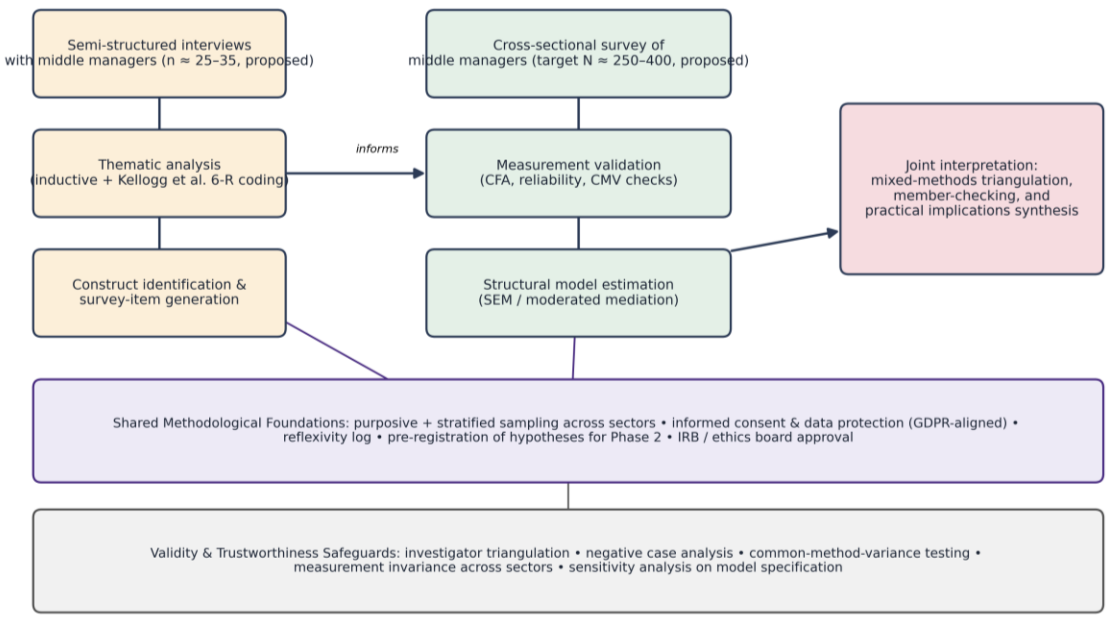

Figure 4: Proposed sequential explanatory mixed-methods research design.

5.2 Study Context and Sampling

The proposed target population is middle managers—defined as managers with both a direct reporting line to senior/executive leadership and formal supervisory responsibility for frontline employees or first-line supervisors—working in organizations that have implemented at least one algorithmic coordination, monitoring, or evaluation system (e.g., workforce scheduling algorithms, performance dashboards, algorithmic routing, or AI-assisted HR analytics). A purposive, stratified sampling strategy is proposed, stratifying by industry sector (e.g., logistics/retail, financial services, technology, healthcare) and by algorithmic management intensity (low/medium/high, assessed via a screening instrument) to ensure variance on the key independent variable. Table 2 summarizes the proposed data sources for both phases. The proposed stratification is intended to capture meaningful variation in organizational contexts and levels of algorithmic integration. Screening criteria will further verify that participants possess sufficient exposure to algorithmically mediated managerial processes to provide informed responses.

This approach also supports comparative analysis across sectors and intensity levels while reducing the risk of sampling a homogeneous managerial population. The resulting sample structure is expected to provide an appropriate basis for examining variation in role ambiguity, strategic influence, and related organizational outcomes. This design further enhances the comparability of responses across organizational and technological contexts.

Table 2: Proposed Data Sources (Recommended for Future Data Collection)

Data Source	Phase	Proposed Size	Content	Sector Scope	Rationale
Semi-structured interviews	1 (Qualitative)	n ≈ 25–35 (proposed)	Role experience, sensemaking, trust in algorithmic outputs	Multi-sector, purposive	Grounds constructs in lived experience; refines survey items
Cross-sectional online survey	2 (Quantitative)	N ≈ 250–400 (proposed)	Validated scales for AMII, RA, DLC, GOV, MMSI, EWE	Multi-sector, stratified	Enables SEM estimation of the structural model in Figure 4
Organizational document review	1 & 2 (Contextual)	5–10 organizations (proposed)	AI governance policies, role descriptions, escalation/appeal procedures	Matched to survey organizations	Validates self-reported GOV construct against documented policy
Follow-up member-checking interviews	3 (Integration)	n ≈ 10–15 (proposed)	Interpretation of quantitative findings	Subsample of Phase 1/2 participants	Strengthens construct validity and practical relevance

5.3 Measures

Table 3 summarizes proposed measurement approaches for each construct. Where possible, items should be adapted from established scales (e.g., role ambiguity from the Rizzo, House, and Lirtzman role-conflict/ambiguity tradition; LMX-7 for relational legitimacy) rather than newly generated, to preserve comparability with prior organizational-behavior research; new items are needed principally for algorithmic management intensity, given the novelty of the construct.

Table 3: Proposed Construct Measurement Approach

Construct	Type	Proposed Measurement Approach	Indicative Source / Basis
Algorithmic Management Intensity (AMII)	Independent variable	New multi-item index across the six mechanisms (restrict, recommend, record, rate, replace, reward), 5-point frequency scale	Adapted from Kellogg et al. (2020) typology
Role Ambiguity (RA)	Mediator	Adapted role-ambiguity subscale, 5-point agreement scale	Established role-theory measurement tradition
AI Governance & Transparency (GOV)	Exogenous/moderator of RA	New scale: presence and clarity of explainability, audit, and appeal mechanisms	Derived from algorithmic-governance literature
Digital Leadership Capability (DLC)	Moderator	Self- and supervisor-rated competency scale (interpreting data, communicating algorithmic outputs)	Adapted from digital-leadership competency literature
Middle-Manager Strategic Influence (MMSI)	Dependent / mediator	Adapted Floyd & Wooldridge strategic-involvement scale (championing, synthesizing, facilitating, implementing)	Floyd & Wooldridge (1992)
Employee Work Engagement (EWE)	Downstream outcome	Short-form validated engagement scale, aggregated at manager–unit level	Established engagement-measurement tradition

5.4 Data Preprocessing and Common-Method-Variance Controls

Proposed preprocessing steps include reverse-scoring checks, attention-check item removal, multivariate outlier screening (Mahalanobis distance), and Harman's single-factor test together with a marker-variable technique to assess common method variance, given that both predictor and outcome constructs would be collected from the same respondents in Phase 2. Where feasible, employee engagement (EWE) should be collected from employees themselves rather than from the managers being rated, to reduce same-source bias on the outcome variable.

6. Mathematical and Statistical Model Specification

This section formalizes the proposed measurement and structural models. All notation is defined at first use; no coefficients are populated with values, since no data have been collected—the equations specify what would be estimated, not what has been found.

6.1 Algorithmic Management Intensity Index

Algorithmic Management Intensity (AMII) for manager i is proposed as a weighted composite across the six mechanisms of algorithmic control:

$$AMII_i = \Sigma_{k=1}^{6} w_k \cdot m_{ik} \tag{1}$$

where m_{ik} is manager i's standardized score on mechanism k (k = restricting, recommending, recording, rating, replacing, rewarding), and w_k is the mechanism weight, initially set to 1/6 (equal weighting) and subsequently re-estimated as factor loadings from a confirmatory factor analysis once data are available.

6.2 Measurement Reliability

Internal consistency of each multi-item scale is to be assessed using Cronbach's alpha,

$$\alpha = \big(n/(n-1)\big) \cdot (1 - \Sigma_i \sigma^2{}_i / \sigma^2{}_x) \quad (2)$$

where n is the number of items, σ^2_i is the variance of item i, and σ^2_x is the variance of the summed scale, and composite reliability (CR) from the confirmatory factor model,

$$CR = (\Sigma_i \lambda_i)^2 / [(\Sigma_i \lambda_i)^2 + \Sigma_i \theta_i] \quad (3)$$

where λ_i is the standardized factor loading of item i and θ_i is its error variance. Proposed acceptability thresholds are $\alpha \geq .70$ and $CR \geq .70$, consistent with conventional organizational-behavior measurement standards.

6.3 Structural (Moderated-Mediation) Model

The structural model in Figure 4 is specified as a moderated-mediation path model. The mediator (role ambiguity) is regressed on the independent variable and the moderator of the a-path:

$$RA_i = a_0 + a_1 \cdot AMII_i + a_2 \cdot GOV_i + a_3 \cdot (AMII_i \times GOV_i) + \Sigma a_j \cdot Z_{ji} + \varepsilon_i \quad (4)$$

The dependent variable (strategic influence) is regressed on the mediator, the independent variable (direct effect), the moderator of the b-path, and their interaction:

$$MMSI_i = b_0 + b_1 \cdot RA_i + b_2 \cdot DLC_i + b_3 \cdot (RA_i \times DLC_i) + c' \cdot AMII_i + \Sigma b_j \cdot Z_{ji} + \zeta_i \quad (5)$$

where Z_{ji} denotes control variables (e.g., organizational tenure, sector, span of control) and c′ is the direct effect tested under H1'. The downstream outcome is regressed on strategic influence: $EWE_i = d_0 + d_1 \cdot MMSI_i + \Sigma d_j \cdot Z_{ji} + \eta_i$ (6)

The conditional indirect effect of AMII on MMSI through RA, at a given level of the moderator DLC, is

$$\theta(DLC) = a_1 \cdot (b_1 + b_3 \cdot DLC) \quad (7)$$

Statistical significance of θ(DLC) is proposed to be assessed via bias-corrected bootstrap confidence intervals (5,000 resamples), consistent with contemporary moderated-mediation practice, rather than the Sobel test, given the latter's normality assumption is frequently violated for indirect-effect distributions.

6.4 Model Fit and Robustness Criteria

Proposed structural equation model fit is to be evaluated using the comparative fit index ($CFI \geq .95$), the root mean square error of approximation ($RMSEA \leq .06$), and the standardized root mean square residual ($SRMR \leq .08$), following conventional joint criteria. Measurement invariance across sectors (configural, metric, and scalar) is to be tested before pooling data across industries, and a multi-group SEM is proposed as a robustness check comparing high- versus low-algorithmic-intensity subsamples.

7. Proposed Evaluation Framework

Because this paper presents a conceptual framework rather than the results of completed data collection, this section describes the proposed evaluation framework and illustrative analytical outputs only. No values below represent real observations, and no claims of statistical significance, effect size, or model superiority are made; all figures are structural placeholders indicating what the analysis pipeline would produce once data are collected. Accordingly, the reported outputs should be understood solely as methodological exemplars that demonstrate how future empirical findings may be organized, evaluated, and interpreted.

7.1 Proposed Evaluation Metrics

Table 4: Proposed Evaluation Metrics for the Structural Model (Illustrative Framework Only)

Analytical Stage	Proposed Metric	Purpose	Acceptability Threshold (Proposed)
Measurement model	Cronbach's α; Composite Reliability (CR)	Internal consistency of multi-item scales	α ≥ .70; CR ≥ .70
Measurement model	Average Variance Extracted (AVE)	Convergent validity	AVE ≥ .50
Measurement model	Heterotrait-Monotrait ratio (HTMT)	Discriminant validity between constructs	HTMT < .85
Structural model	CFI, RMSEA, SRMR	Overall model fit	CFI ≥ .95; RMSEA ≤ .06; SRMR ≤ .08
Structural model	Standardized path coefficients (H1–H5)	Direction and strength of hypothesized relationships	Bootstrap 95% CI excluding zero
Structural model	Conditional indirect effect θ(DLC)	Moderated-mediation significance (Eq. 7)	Bias-corrected bootstrap CI excluding zero
Robustness	Measurement invariance (configural/metric/scalar)	Cross-sector comparability	ΔCFI ≤ .01 across nested models
Robustness	Common-method-variance marker test	Rule out same-source inflation	Marker-adjusted correlations largely unchanged

7.2 Illustrative (Non-Empirical) Interpretation Template

To make the analytical plan concrete, Table 5 presents a proposed ablation-style component analysis: a template for assessing how much explanatory contribution each element of the structural model would add, to be populated once real data are analyzed. All entries are placeholders ("TBD") rather than results.

Table 5: Proposed Component (Ablation-Style) Analysis Template — To Be Populated with Real Data

Model Configuration	**AMII → RA (a_1)**	**RA → MMSI (b_1)**	**MMSI → EWE (d_1)**	**Model R^2 (MMSI)**	**ΔR^2 vs. Full Model**
Full model (H1–H5, with GOV and DLC moderators)	TBD	TBD	TBD	TBD	— (reference)
Without GOV moderator (H3 removed)	TBD	TBD	TBD	TBD	TBD
Without DLC moderator (H5 removed)	TBD	TBD	TBD	TBD	TBD
Direct-effect-only model (RA mediator removed)	—	—	TBD	TBD	TBD

Note. "TBD" entries denote values to be determined empirically; they are not omitted or rounded real findings. This table is included to specify the analytical logic of the proposed ablation strategy, not to report outcomes.

8. Discussion

Although the framework proposed here has not yet been empirically tested, its structure yields several interpretable implications when read against the literature reviewed in Section 2. First, the framework predicts that algorithmic management's effect on middle-manager influence is indirect rather than direct—operating through role ambiguity rather than mechanically displacing managers. This is consistent with Jarrahi et al.'s (2021) observation that algorithmic management "can also decrease the power and agency of individual managers" without necessarily eliminating the managerial layer itself, and with Raisch and Krakowski's (2021) argument that automation and augmentation coexist rather than substitute cleanly for one another.

Second, the inclusion of AI governance and transparency (GOV) as a direct antecedent of role ambiguity, independent of algorithmic management intensity, implies that organizations facing similar levels of algorithmic delegation could produce markedly different managerial experiences depending on the quality of their explainability and appeal mechanisms. This prediction is consistent with the divergent outcomes Vieira and Junte (2025) document between coercive and relationally embedded algorithmic deployments in the same sector, suggesting that governance design, not algorithmic capability per se, may be the more tractable lever for organizations seeking to preserve managerial legitimacy.

Third, the moderating role hypothesized for digital leadership capability (DLC) positions leadership development, rather than algorithmic restraint, as the primary practical lever available to organizations: because algorithmic delegation is unlikely to reverse, the framework implies that organizations should invest in managers' capacity to interpret and contextualize algorithmic outputs rather than in resisting delegation itself. This is consistent with the general thrust of the augmentation literature (Raisch & Krakowski, 2021) and with Davenport and Mittal's (2020) argument that data-driven culture change must be actively led, not merely technologically enabled.

Unexpected or counterintuitive findings, should future data reveal a positive rather than negative direct effect (c' in Equation 5) of algorithmic management intensity on strategic influence, would suggest that some managers reinterpret algorithmic systems as evidentiary resources that strengthen their championing and synthesizing activity rather than threats to their authority—an outcome consistent with algorithm-appreciation findings in adjacent literatures (e.g., conditions under which transparency increases reliance; Dietvorst et al., 2018) and worth explicit testing rather than assumption.

9. Explainability and Interpretability Considerations

Because the central phenomenon under study is managers' interpretation of algorithmic outputs, explainability is not only a technical property of the algorithmic systems under study but a substantive construct within the framework itself (operationalized within GOV, Section 3.2). Four considerations follow.

i. Local versus global interpretability: middle managers typically require local explanations (why did the system flag this employee or this schedule conflict) rather than global model behavior, since their decisions are case-specific; the proposed GOV measure should therefore weight case-level explanation availability more heavily than aggregate model documentation.

ii. Feature-importance and counterfactual explanations, where the underlying algorithmic systems support them, are proposed as the qualitative material to be coded in Phase 1 interviews when assessing how managers describe their trust-building process, rather than treated as a separate technical evaluation of the algorithms themselves (which are not the object of study here).

iii. Benefits and limits: transparency can reduce role ambiguity (H3) by clarifying why a recommendation was made, but excessive technical detail can itself increase perceived complexity and, per algorithm-aversion research, reduce reliance if managers cannot reconcile explanations with intuitive judgment (Dietvorst et al., 2015).

iv. Attention to power, not only accuracy: consistent with Kellogg et al. (2020), explainability provisions should be evaluated not only for whether they clarify algorithmic logic but for whether they restore managers' and employees' practical capacity to contest or appeal algorithmic outputs—explanation without appeal risks legitimating rather than checking algorithmic authority.

10. Ethics, Governance, and Privacy Considerations

The proposed study and the organizational phenomenon it examines both raise governance questions that must be addressed explicitly rather than treated as incidental.

10.1 Research Ethics

The proposed protocol requires institutional ethics board approval before data collection; informed consent covering the purpose, voluntary nature, and data-handling procedures of participation; anonymization of interview transcripts and survey responses at the point of collection; secure, access-controlled data storage; and a clear data-retention and deletion policy aligned with applicable data-protection regulation (e.g., GDPR-equivalent standards) in the jurisdictions where data collection occurs. Because Phase 2 proposes collecting employee engagement data separately from managerial self-reports to reduce common-method variance (Section 5.4), particular care is required to prevent employees' responses from being traceable back to identifiable managers in ways that could expose either party to retaliation.

10.2 Organizational AI Governance

At the level of the phenomenon under study, the framework treats AI governance and transparency (GOV) as a construct with normative as well as explanatory significance. Consistent with responsible-AI principles, organizations implementing algorithmic management systems should provide documented decision criteria, audit trails, and functioning appeal mechanisms for employees and managers affected by algorithmic outputs; should assess algorithmic systems for disparate impact across protected groups before and after deployment; and should assign clear accountability for algorithmic errors rather than allowing accountability to diffuse across human and automated actors, a risk Kellogg et al. (2020) identify as a defining feature of contested algorithmic terrain.

10.3 Bias, Fairness, and Data Governance

Although this paper does not itself audit any specific algorithmic system, the proposed measurement of algorithmic management intensity (Section 6.1) should be accompanied, in any future data collection, by documentation of the underlying systems' training data provenance, update frequency, and known limitations, since these properties plausibly moderate how much trust managers place in algorithmic recommendations independent of the governance and transparency provisions captured by GOV.**11. Robustness and Validity**

11.1 Internal Validity

The cross-sectional design proposed for Phase 2 limits causal inference; the moderated-mediation model in Section 6.3 should therefore be interpreted as a theoretically ordered association structure rather than a strict causal test, unless a longitudinal or quasi-experimental extension (Section 13) is implemented. Common-method-variance controls (Section 5.4) and separation of outcome and predictor sources partially mitigate, but do not eliminate, this limitation.

11.2 External Validity

Purposive, stratified sampling across sectors is proposed to support generalizability, but the framework's applicability to public-sector, unionized, or highly regulated environments—where managerial authority and algorithmic deployment operate under different legal constraints—would require separate validation and is flagged as a boundary condition rather than assumed.

11.3 Measurement Validity

Because the AMII construct is newly proposed, its content and construct validity should be established through the Phase 1 qualitative work before quantitative deployment, including expert review of item content and pilot testing with cognitive interviews. Measurement invariance testing (Section 6.4) is proposed as a precondition for any cross-sector comparison of structural paths.

11.4 Distribution Shift and Model Drift

Because algorithmic management systems themselves evolve over time (e.g., through retraining or vendor updates), the AMII construct is time-indexed by design, and any longitudinal extension of this framework should treat algorithmic system changes as a documented covariate rather than an assumed constant, to avoid conflating organizational role change with underlying algorithmic drift.

12. Limitations

i. No primary data have been collected; the framework, hypotheses, and evaluation plan presented here are theoretical and require empirical validation before any causal or predictive claims can be made.

ii. The proposed sample sizes (Table 2) are indicative planning estimates based on conventional SEM power guidelines, not the result of a formal a priori power analysis conducted against pilot effect-size estimates, which should precede actual data collection.

iii. The newly proposed Algorithmic Management Intensity construct has not undergone psychometric validation; its dimensionality (a single composite versus six correlated mechanism-level factors) is an open empirical question.

iv. The framework focuses on middle managers as the unit of analysis and does not directly model frontline employees' independent experience of algorithmic management, beyond the single downstream engagement outcome (EWE); a fuller account would require a multi-level design.

v. Cross-sectional data, if collected as proposed, cannot establish the temporal precedence required for strong causal claims about role ambiguity as a mediating mechanism.

vi. The literature synthesized in Section 2 is concentrated in North American and European organizational contexts; cross-cultural generalizability of both the framework and the underlying middle-management and algorithmic-management literatures is not established.

vii. Reliance on self-reported measures for several constructs (AMII, RA, DLC) introduces potential social-desirability bias, particularly for items touching on trust in or resistance to organizational technology.

viii. 13. Future Research Directions

ix. Longitudinal panel studies tracking the same middle managers across the phased introduction of an algorithmic management system, enabling stronger causal inference than the cross-sectional design proposed here.

x. Multi-level modeling that nests frontline employee engagement within managerial units and managerial units within organizations, to separate manager-level from organization-level sources of variance in the outcomes examined.

xi. Cross-national replication of the AMII construct and structural model in labor-market and regulatory contexts with stronger statutory protections around algorithmic decision-making (e.g., EU AI Act-governed contexts), to test the boundary conditions flagged in Section 11.2.

xii. Comparative case studies of organizations that deliberately invest in digital leadership capability (DLC) development versus those that do not, to complement the survey-based moderation test with process-level evidence of how capability development occurs.

xiii. Integration with algorithm-aversion experimental paradigms (building on Dietvorst et al., 2015, 2018) to test whether manipulating algorithmic transparency or manager control over algorithmic outputs causally reduces role ambiguity, extending the correlational GOV–RA path (H3) proposed here.

xiv. Extension of the framework to examine algorithmic management's effects on middle-manager well-being and turnover intention, which the present framework does not model but which the literature on middle-manager burnout suggests may be a consequential downstream outcome.

xv. Field experiments partnering with organizations piloting explainable-AI interfaces for managerial dashboards, to test the interpretability considerations raised in Section 9 under real operating conditions rather than self-report alone.

14. Reproducibility Statement

As no empirical data were collected for this conceptual paper, code and dataset availability statements are not applicable. To support future reproducibility, the following are specified in full within this paper: the complete set of theoretical constructs and their proposed operational definitions (Section 3.2); the complete structural and measurement model equations (Section 6); the proposed sampling frame, instruments, and data sources (Section 5, Tables 2–3); and the proposed model-fit and validity thresholds (Section 6.4, Table 4). Researchers implementing this design are encouraged to pre-register the hypotheses in Section 4 and the analysis plan in Section 6 prior to data collection, and to report software, package versions (e.g., lavaan or Mplus for SEM, R or Python version), and random seeds used for bootstrap resampling once analyses are conducted.

15. Conclusion

This paper set out to address a specific gap: the absence of an integrated, testable framework explaining how algorithmic management reshapes the middle-management layer in organizations pursuing data-driven decision cultures. Synthesizing algorithmic-management, middle-management, data-driven-culture, and human-AI collaboration literatures, the paper developed a conceptual framework in which algorithmic management intensity operates on middle managers' strategic influence indirectly, through role ambiguity, moderated by organizational AI governance and by managers' own digital leadership capability, with consequences for frontline employee engagement. Five formal hypotheses (H1–H5) and a complete moderated-mediation model specification (Equations 1–7) translate this framework into a form suitable for empirical estimation, and a sequential explanatory mixed-methods design, sampling strategy, and measurement plan are proposed to test it.

The central theoretical claim advanced here—that algorithmic management redefines rather than simply displaces middle-management work—directly answers the paper's guiding research questions: algorithmic systems change what middle managers do (interpreting, contextualizing, and legitimating algorithmic outputs rather than solely directing and evaluating subordinates directly) and how much influence they retain, with governance and leadership capability, not algorithmic capability alone, as the principal levers available to organizations. Practically, the framework implies that organizations implementing algorithmic management should treat middle-manager role redesign, explainability provisioning, and digital-leadership development as coupled investments rather than sequential afterthoughts to algorithmic deployment. Academically, the paper contributes a theory-grounded bridge between literatures that have so far developed largely in parallel, and a reproducible protocol for testing that bridge empirically.

As with any conceptual contribution, the value of this framework rests on its empirical falsifiability. The proposed methodology, measurement approach, and structural model are offered specifically to enable that test, and the paper's limitations (Section 12) and future research agenda (Section 13) are intended as a concrete starting point for the empirical program this framework requires.

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