Scholedge International Journal of *Management & Development*
ISSN 2394-3378 Vol. 13, Issue 02 (2026)
DOI: https://dx.doi.org/10.19085/sijmd130202

Beyond Hybrid Work: Designing High-Performance Organizations in the Age of AI

R. Narenderajan
HR & Recruiting Consultant, Chennai, India

ABSTRACT

Hybrid work models developed largely in response to workplace disruptions caused by the COVID-19 pandemic, treating location flexibility as the central organizing question. This paper argues that artificial intelligence has moved the debate past questions of where work happens toward questions of how work is structured, decided, and governed. Drawing on Dynamic Capabilities Theory, the Resource-Based View, Knowledge-Based View, Sociotechnical Systems Theory, Organizational Learning Theory, Contingency Theory, and Human Capital Theory, the paper develops a conceptual framework linking AI capability, organizational agility, human-AI collaboration, leadership capability, employee empowerment, organizational learning, innovation performance, and organizational performance. The paper examines how AI reshapes managerial decision-making by distinguishing decision augmentation from decision automation, and considers the governance tensions between centralized and decentralized approaches to AI deployment. It also considers how algorithmic management affects trust, autonomy, and engagement among employees, and identifies the leadership competencies that gain value once routine managerial tasks are delegated to algorithmic systems. Because the paper is conceptual, it proposes a research design using PLS-SEM to test the relationships identified, along with measurement constructs, sampling considerations, and reliability and validity procedures for a future empirical study. The paper closes with implications for managers, policy makers, and organizational designers, and identifies open questions that current literature has not resolved, including the long-term effects of algorithmic management on organizational trust and the conditions under which decentralized AI governance outperforms centralized models. The paper does not report new empirical data. Its contribution lies in integrating separate streams of research on AI adoption, organizational design, and leadership into a single framework intended to guide subsequent empirical testing.

Keywords: Artificial intelligence, organizational design, hybrid work, human-ai collaboration, digital leadership, algorithmic management, organizational agility, innovation performance

INTRODUCTION

When organizations shifted to remote and hybrid arrangements after 2020, most of the resulting research and practitioner literature treated the change as one of location: who could work from home, how often, and under what scheduling rules. That framing served its purpose in the short term, but it left unexamined a larger question now confronting organizations. Artificial intelligence systems that draft documents, screen candidates, forecast demand, allocate tasks, and take part in decisions once reserved for managers are changing the underlying architecture of organizations, not just where employees sit while they work.

This shift raises questions that hybrid work research was not built to answer. If a scheduling algorithm rather than a supervisor decides who takes which shift, what happens to employee trust in management? If an AI system can draft a strategic recommendation as quickly as a mid-level manager, what remains for that manager to do, and what new skills does the role require? If decision-making authority moves toward algorithmic systems, should governance of those systems sit with a central data science function or be distributed across business units closer to the decisions being made? These questions concern organizational design directly: reporting structures, decision rights, skill requirements, and the distribution of trust and accountability across human and machine actors.

The management literature has produced a fair amount of work on AI adoption in specific functions such as recruitment, supply chain forecasting, and customer service, and a separate body of work on hybrid and remote work arrangements. Fewer studies connect these two streams to ask how AI reshapes the organization as a whole, including its leadership requirements, its learning processes, and its capacity to sustain performance under conditions of ongoing technological change. Dynamic Capabilities Theory offers language for describing how organizations sense, seize, and reconfigure resources in response to change, but has been applied to AI adoption unevenly across the literature. The Resource-Based View and Knowledge-Based View explain why AI capability might function as a source of advantage, yet neither addresses directly how that capability interacts with human judgment inside day-to-day operations. Sociotechnical Systems Theory, which treats technical and social subsystems as jointly determining organizational outcomes, fits this problem well but appears less often in current AI management research than it did in earlier waves of technology adoption research from the 1990s and 2000s.

This paper works from the premise that AI-enabled organizational design deserves treatment as a distinct research problem, separate from both the hybrid work literature and function-specific AI adoption studies. It proposes a conceptual framework linking AI capability, organizational agility, human-AI collaboration, leadership capability, employee empowerment, organizational learning, innovation performance, and organizational performance, grounded in the theoretical traditions named above. The paper distinguishes decision augmentation, where AI systems support human judgment, from decision automation, where AI systems replace human judgment for defined categories of decisions, and treats this distinction as central to questions of governance, accountability, and trust. It also considers where responsibility for AI governance should sit within an organization, given competing arguments for centralized oversight and for decentralized, business-unit-level control.

The paper is organized as follows. After reviewing relevant literature and identifying the gap this study addresses, it sets out research objectives and questions, followed by theoretical foundations and the conceptual framework. Propositions linking the framework's constructs are then developed. A research methodology section proposes an empirical design suited to testing these propositions, since the present paper is conceptual and does not report primary data. The paper closes with managerial and policy implications, practical recommendations, limitations, and directions for future research.

LITERATURE REVIEW

From remote work to hybrid work: the boundaries of existing research

The hybrid work literature that expanded after 2020 concentrated on a narrow set of questions: how often employees should attend a physical office, how managers should evaluate productivity without direct observation, and how organizations could preserve culture and collaboration across dispersed teams. Cascio and Montealegre (2016) had already argued, before the pandemic accelerated these debates, that technology changes work along several dimensions at once, including where work happens, who performs it, and how it gets coordinated, not location alone. Their review treated technology as a force reshaping job design and organizational structure, which places the hybrid work conversation inside a longer-running stream of research on technology and organizational form rather than treating it as a self-contained topic.

Much of the pandemic-era hybrid work literature did not extend this framing. Studies tended to isolate location and scheduling as the variables of interest, measuring outcomes such as employee satisfaction, perceived flexibility, and self-reported productivity. This body of work answered real organizational questions during a period of disruption, but it left the deeper structural question mostly untouched: whether AI systems performing coordination, evaluation, and decision tasks change the organization's design independent of where employees are physically located. An organization could resolve every hybrid work question and still face a separate set of design problems introduced by algorithmic scheduling, automated performance evaluation, or AI-assisted strategic planning.

AI and organizational structure

Research on AI and organizational structure draws heavily on Dynamic Capabilities Theory, originally developed by Teece, Pisano, and Shuen (1997) and extended by Teece (2007) to describe how firms sense opportunities, seize them through resource reconfiguration, and transform internal structures to sustain advantage under changing conditions. Applied to AI adoption, this framework suggests that firms capable of continuously reconfiguring roles, workflows, and reporting relationships around evolving AI capabilities should outperform firms that treat AI as a fixed tool bolted onto existing structures. Von Krogh (2018) made a related argument specifically about organizational design, proposing that AI functions as an organizational phenomenon in its own right rather than a purely technical one, and that its inputs, processes, and outputs need to be theorized at the level of the organization rather than the individual task.

The Resource-Based View, associated with Barney (1991), and the Knowledge-Based View articulated by Grant (1996), offer a different but complementary lens. Both treat firm-specific resources, including proprietary knowledge and organizational routines, as sources of competitive advantage that are difficult for competitors to replicate. Applied to AI, this suggests that generic access to AI tools confers little advantage on its own, since competitors can acquire similar tools. What distinguishes firms is how effectively they integrate AI outputs with existing organizational knowledge and routines, a point consistent with Grant's original argument that firm advantage rests on the integration of specialized knowledge rather than its mere possession. Krakowski, Luger, and Raisch (2023) extended this line of reasoning specifically to AI, arguing that competitive advantage increasingly depends on how firms combine AI-based prediction capabilities with complementary organizational assets such as data infrastructure, domain expertise, and decision rights, rather than on AI adoption alone.

Sociotechnical Systems Theory, originating with Trist and Bamforth's (1951) work on coal mining and developed further in later applications to information technology, argues that technical and social subsystems must be jointly optimized rather than designed separately. This theory is directly relevant to AI adoption because it resists a common tendency in practitioner literature to treat AI implementation as a purely technical exercise. Parker and Grote (2022) applied sociotechnical thinking specifically to automation and algorithmic technologies, arguing that work design mediates whether digital technologies improve or degrade job resources such as autonomy, skill use, and feedback, and job demands such as performance monitoring. Their central claim is that the effects of AI on employees depend less on the technology itself than on how organizations redesign roles and processes around it, a claim that pushes back against deterministic accounts in which AI's effects on work are treated as fixed by the technology's technical properties.

Decision augmentation versus decision automation

A central distinction running through recent AI management scholarship separates decision augmentation, in which AI systems support human judgment without replacing it, from decision automation, in which AI systems make and execute decisions within defined boundaries with limited human involvement. Raisch and Krakowski (2021) developed this distinction explicitly, describing what they termed the automation-augmentation paradox: organizations that pursue automation and augmentation simultaneously, rather than choosing one over the other, face a paradoxical tension because the two applications are interdependent across time and space. Their argument challenges the common practitioner advice to simply prioritize augmentation over automation for superior performance. Instead, they contend that overemphasizing either approach in isolation produces reinforcing cycles with negative organizational consequences, and that organizations need a broader perspective that accommodates both to achieve complementary benefits.

Davenport and Ronanki (2018) reached a related conclusion from a more applied angle, reporting that organizations pursuing AI initiatives achieved better outcomes when they targeted augmentation of specific tasks within existing roles rather than wholesale automation of entire job categories. This finding aligns with Jarrahi's (2018) argument that AI and human cognition bring complementary strengths to organizational decision-making: AI systems handle large-scale pattern recognition and consistency well, while humans retain advantages in contextual judgment and handling situations marked by uncertainty and equivocality that fall outside historical data patterns. Jarrahi frames this complementarity as a reason to design AI-human collaboration deliberately rather than treating AI as a straightforward substitute for human labor.

Algorithmic management, trust, and employee autonomy

A separate stream of research examines how employees respond when algorithmic systems take on managerial functions such as task assignment, performance evaluation, and scheduling. Kellogg, Valentine, and Christin (2020) reviewed this literature and organized it around six mechanisms through which algorithms shape work, which they termed restricting, recommending, recording, rating, replicating, and rewarding. Their review found that algorithmic management often increases efficiency and consistency but can also reduce employees' sense of control, particularly when the logic behind algorithmic decisions is not visible to the people affected by them. This connects to a wider concern in the organizational justice literature about procedural transparency: decisions perceived as arbitrary or unexplainable tend to erode trust even when their outcomes are objectively reasonable.

This creates a design tension for organizations adopting AI in managerial functions. Systems that improve consistency and reduce certain forms of human bias may simultaneously introduce a different problem: employees who cannot understand or contest algorithmic decisions may disengage or resist, undermining the efficiency gains the system was meant to produce. Kellogg et al. note that outcomes vary considerably depending on how much explanation and recourse organizations build into algorithmic systems, suggesting that the technology itself does not determine trust outcomes; the surrounding governance and communication practices do.

Leadership under AI-enabled conditions

As routine managerial tasks move toward automation or augmentation, the literature on digital leadership has begun to ask what remains distinctly valuable about human management. This work remains less developed than the structural and algorithmic management literatures discussed above, and much of it draws on adjacent research from earlier waves of digital transformation rather than AI specifically. The general direction of this literature suggests that as AI systems absorb tasks involving routine analysis, scheduling, and reporting, the competencies that retain or gain value include judgment under ambiguity, decisions in situations without clear precedent, and the interpersonal work of building trust among employees who may feel uncertain about their own role security. This is consistent with the broader argument from Raisch and Krakowski (2021) and Jarrahi (2018) that human contribution retains distinct value precisely where situations diverge from historical patterns that AI systems were trained on.

Organizational learning and human capital under AI adoption

Organizational Learning Theory, developed through the work of Argyris and Schön (1978), distinguishes single-loop learning, which corrects errors within existing routines, from double-loop learning, which questions and revises the underlying assumptions behind those routines. AI adoption arguably demands more double-loop learning than typical technology adoption, since it can call into question not just how tasks are performed but which tasks belong to human roles at all. Organizations that treat AI adoption as a single-loop problem, meaning they simply insert AI tools into existing workflows without reconsidering the workflows themselves, may fail to realize the structural benefits that Teece's dynamic capabilities framework associates with successful adaptation.

Human Capital Theory, tracing to Becker (1964), frames employee skills and knowledge as a form of capital that generates returns for both the individual and the organization. Applied to AI adoption, this raises questions about which skills organizations should invest in developing as AI absorbs routine tasks. The literature reviewed here does not offer a settled answer. Some scholars argue for investment in technical AI literacy across the workforce, while others, following the augmentation logic of Jarrahi (2018) and Raisch and Krakowski (2021), argue that investment should concentrate on distinctly human capabilities such as judgment and interpersonal skill, on the reasoning that these are the areas where human contribution remains hardest to replicate.

Synthesis

Taken together, this literature suggests several things relevant to the present paper. First, the hybrid work literature and the AI adoption literature have developed largely in parallel, with limited integration between questions of physical location and questions of decision authority and organizational structure. Second, the distinction between decision augmentation and decision automation appears repeatedly across multiple theoretical traditions and offers a useful organizing concept for thinking about organizational design choices under AI adoption. Third, the algorithmic management literature identifies trust and transparency as central variables that mediate whether AI adoption improves or damages organizational functioning, a point not fully captured by structural theories such as the Resource-Based View or Dynamic Capabilities Theory on their own. Fourth, questions about leadership competency under AI-enabled conditions remain comparatively underdeveloped relative to the structural and algorithmic management literatures, leaving open questions about which specific capabilities organizations should prioritize in leadership development as routine managerial tasks shift toward automation.

RESEARCH GAP

Three gaps emerge from this review. The existing literature treats hybrid work arrangements and AI-driven organizational change as largely separate research problems, despite both concerning the same underlying question of how decision authority and coordination are distributed across an organization. Structural theories such as Dynamic Capabilities Theory and the Resource-Based View explain why AI capability might generate advantage but do not adequately address how trust and employee experience mediate that relationship, a gap the algorithmic management literature partially addresses without connecting back to firm-level performance outcomes. Leadership competency requirements under AI-enabled conditions remain underspecified compared to the more developed literatures on organizational structure and algorithmic management, leaving open questions about which specific capabilities organizations should prioritize in leadership development as routine managerial tasks shift toward automation.

This paper addresses these gaps by integrating structural, behavioral, and leadership perspectives into a single conceptual framework, and by treating decision augmentation versus automation as a design variable that connects organizational structure to employee trust and, ultimately, to performance outcomes.

RESEARCH OBJECTIVES

1. To examine how artificial intelligence is reshaping the conceptual boundaries of hybrid work beyond questions of physical location.
2. To identify the organizational capabilities that distinguish high-performing AI-enabled organizations from organizations that adopt AI without corresponding structural change.
3. To determine which leadership competencies gain relative value as AI systems assume routine managerial tasks.
4. To propose principles for redesigning work processes in ways that maintain employee trust and engagement under increased AI involvement in decision-making.
5. To identify governance mechanisms that support responsible AI adoption at the organizational level.
6. To develop and justify a conceptual framework linking AI capability, organizational agility, human-AI collaboration, leadership capability, employee empowerment, organizational learning, innovation performance, and organizational performance.

RESEARCH QUESTIONS

RQ1: How is artificial intelligence changing the concept of hybrid work?

RQ2: What organizational capabilities distinguish high-performing AI-enabled organizations?

RQ3: Which leadership competencies become more valuable as AI assumes routine managerial tasks?

RQ4: How should organizations redesign work processes while maintaining employee engagement and trust?

RQ5: What governance mechanisms are necessary to ensure responsible AI adoption?

THEORETICAL FOUNDATIONS

Dynamic Capabilities Theory

Dynamic Capabilities Theory, developed by Teece, Pisano, and Shuen (1997) and extended by Teece (2007), describes the processes through which firms sense opportunities and threats, seize opportunities through resource reconfiguration, and transform internal and external competencies to address changing environments. This paper uses the theory to explain how organizations build AI capability over time rather than treating it as a one-time acquisition. Sensing corresponds to identifying where AI can plausibly improve decision quality or efficiency; seizing corresponds to committing resources to specific AI applications and the process redesign that accompanies them; transforming corresponds to the ongoing reconfiguration of roles, structures, and routines as AI applications mature and expand. The theory provides the paper's central justification for treating AI capability as a dynamic, evolving organizational property rather than a fixed technical asset.

Resource-Based View and Knowledge-Based View

The Resource-Based View (Barney, 1991) holds that sustained competitive advantage arises from resources that are valuable, rare, difficult to imitate, and non-substitutable. The Knowledge-Based View (Grant, 1996) extends this logic by treating knowledge, and the organization's capacity to integrate specialized knowledge across individuals, as the primary basis for advantage. Applied to this paper's framework, these theories explain why AI capability alone does not guarantee superior performance. Firms that acquire similar AI tools but fail to integrate them with existing organizational knowledge, or that fail to develop firm-specific routines around AI use, should not expect to sustain advantage from AI adoption. This reasoning supports the paper's treatment of human-AI collaboration and organizational learning as necessary intervening variables between AI capability and performance outcomes, consistent with Krakowski, Luger, and Raisch's (2023) argument that competitive advantage under AI adoption depends on the combination of prediction capability with complementary organizational assets.

Sociotechnical Systems Theory

Sociotechnical Systems Theory, originating with Trist and Bamforth (1951), argues that organizational performance depends on the joint optimization of technical systems and social systems, rather than optimizing either in isolation. Parker and Grote (2022) apply this reasoning directly to digital technologies including AI, arguing that work design choices determine whether AI improves or degrades employee experience and performance. This paper uses Sociotechnical Systems Theory to justify including human-AI collaboration and employee empowerment as central constructs in the conceptual framework, rather than treating AI capability as a variable that acts on performance independent of how work itself is designed around it.

Organizational Learning Theory

Organizational Learning Theory, developed by Argyris and Schön (1978), distinguishes single-loop learning from double-loop learning. This paper uses the distinction to argue that AI adoption requires organizations to engage in double-loop learning, questioning not just how existing tasks are performed but which tasks and decisions belong to human roles under changed technological conditions. Organizational learning functions in the conceptual framework as a mechanism that converts AI capability and human-AI collaboration into innovation performance over time, rather than as a one-time adjustment.

Contingency Theory

Contingency Theory holds that there is no single best way to organize, and that effective organizational design depends on fit between structure and contextual factors such as environmental uncertainty, task interdependence, and technology. This paper applies Contingency Theory to argue that the appropriate balance between decision automation and decision augmentation, and between centralized and decentralized AI governance, is not fixed but depends on factors such as task structure, the stakes of individual decisions, and the maturity of an organization's AI capability. This theoretical position underlies the paper's treatment of governance choices as context-dependent design decisions rather than universal prescriptions.

Human Capital Theory

Human Capital Theory, associated with Becker (1964), treats employee skills and knowledge as a form of capital yielding returns to both the individual and the firm. This paper uses Human Capital Theory to support the inclusion of leadership capability and employee empowerment as constructs distinct from AI capability itself, on the reasoning that AI capability without corresponding investment in human skill development is unlikely to translate into sustained organizational performance.

CONCEPTUAL FRAMEWORK

The conceptual framework proposed in this paper links eight constructs: AI Capability, Organizational Agility, Human-AI Collaboration, Leadership Capability, Employee Empowerment, Organizational Learning, Innovation Performance, and Organizational Performance.

AI Capability refers to an organization's ability to acquire, deploy, and effectively use AI systems across relevant functions, encompassing technical infrastructure, data quality, and organizational routines for integrating AI outputs into decisions. Drawing on Dynamic Capabilities Theory, AI Capability is positioned as an antecedent condition rather than an outcome, one that must be continually renewed as technology and organizational needs change.

Organizational Agility refers to the organization's capacity to sense changes in its environment and reconfigure resources, structures, and processes in response. The framework proposes that AI Capability contributes to Organizational Agility by expanding the range and speed of information available for sensing and by supporting faster reconfiguration of workflows, consistent with the sensing, seizing, and transforming processes described by Teece (2007).

Human-AI Collaboration refers to the degree to which AI systems and human employees jointly participate in task execution and decision-making, encompassing both decision augmentation and decision automation as distinct modes of collaboration. Following Raisch and Krakowski (2021), the framework treats this construct as inherently containing tension between automation and augmentation rather than as a single continuous variable, since organizations typically deploy both modes concurrently across different tasks.

Leadership Capability refers to the competencies leaders bring to managing AI-enabled organizations, including judgment under ambiguity and the capacity to build trust among employees affected by algorithmic systems. The framework proposes that Leadership Capability moderates the relationship between AI Capability and Employee Empowerment, since the same AI system can be deployed in ways that expand or restrict employee autonomy depending on how leaders design its use, consistent with Kellogg, Valentine, and Christin's (2020) finding that outcomes depend heavily on surrounding governance and communication practices rather than on the technology alone.

Employee Empowerment refers to employees' perceived autonomy, competence, and influence over their own work under conditions of AI-assisted management. The framework positions this construct as a consequence of both Human-AI Collaboration design choices and Leadership Capability, consistent with the algorithmic management literature's finding that transparency and recourse mechanisms shape whether algorithmic oversight is experienced as supportive or restrictive.

Organizational Learning refers to the organization's capacity to revise its assumptions and routines in response to experience with AI systems, distinguishing single-loop adjustments from double-loop reconsideration of underlying work design, following Argyris and Schön (1978).

Innovation Performance refers to the organization's output of new products, services, or process improvements attributable in part to AI-enabled capabilities.

Organizational Performance refers to overall firm-level outcomes, including financial performance, operational efficiency, and market responsiveness.

The framework proposes that AI Capability influences Organizational Performance through two parallel paths. The first path runs through Organizational Agility, reflecting the structural and resource-reconfiguration logic of Dynamic Capabilities Theory. The second path runs through Human-AI Collaboration, Employee Empowerment, and Organizational Learning, reflecting the sociotechnical and human capital logic described above. Leadership Capability is positioned as a moderating construct affecting the strength of the relationship between Human-AI Collaboration and Employee Empowerment, and Innovation Performance is positioned as a mediating construct between Organizational Learning and Organizational Performance.

PROPOSITION DEVELOPMENT

Because this paper is conceptual, the relationships identified in the framework are developed as propositions intended to guide future empirical testing rather than as hypotheses tested against collected data.

P1: AI Capability is positively associated with Organizational Agility.

This proposition follows from Dynamic Capabilities Theory. Organizations with stronger AI capability should sense environmental changes more quickly and reconfigure resources more efficiently, consistent with Teece's (2007) description of sensing and seizing processes.

P2: AI Capability is positively associated with Human-AI Collaboration.

Organizations with more developed AI capability are better positioned to deploy AI in ways that meaningfully involve AI systems in task execution and decision support, rather than deploying AI in superficial or isolated applications.

P3: Human-AI Collaboration is positively associated with Employee Empowerment, and this relationship is moderated by Leadership Capability.

Drawing on Kellogg, Valentine, and Christin (2020), the framework proposes that Human-AI Collaboration does not have a uniform effect on Employee Empowerment. Where Leadership Capability is high, meaning leaders design AI deployment with transparency and recourse mechanisms, Human-AI Collaboration is expected to strengthen Employee Empowerment. Where Leadership Capability is low, the same collaboration arrangements may weaken Employee Empowerment by increasing perceived surveillance and reducing perceived control.

P4: Employee Empowerment is positively associated with Organizational Learning.

Employees who perceive greater autonomy and influence over their work are more likely to surface the kind of experiential feedback that supports double-loop learning, following Argyris and Schön (1978).

P5: Organizational Agility is positively associated with Organizational Performance.

P6: Organizational Learning is positively associated with Innovation Performance, and Innovation Performance is positively associated with Organizational Performance.

P7: The relationship between AI Capability and Organizational Performance is stronger when organizations pursue both decision augmentation and decision automation deliberately, consistent with the automation-augmentation paradox described by Raisch and Krakowski (2021), than when organizations pursue either mode exclusively.

RESEARCH METHODOLOGY

Because this paper develops a conceptual framework, the following methodology is proposed for subsequent empirical validation rather than reporting results from data already collected.

Research Philosophy

A post-positivist research philosophy is proposed, treating organizational constructs such as AI Capability and Organizational Agility as measurable through validated survey instruments while acknowledging that measurement is imperfect and that findings should be interpreted probabilistically rather than as deterministic laws.

Research Approach

A deductive, quantitative approach is proposed, since the propositions developed above are derived from established theory and are intended for empirical testing rather than exploratory theory-building. A future study could complement this with a qualitative phase, such as interviews with senior leaders, to interpret unexpected quantitative findings, though the core design proposed here is quantitative.

Sampling Strategy

A purposive sampling strategy targeting mid-to-large organizations that have implemented AI systems in at least one core business function is proposed. Respondents should include managers and employees across multiple organizational levels to capture variation in Leadership Capability and Employee Empowerment, since single-respondent-per-organization designs would not allow within-organization comparison. A target sample of 300 to 400 respondents across at least 40 organizations is proposed, sufficient for PLS-SEM analysis given the model's complexity, following common guidance that PLS-SEM requires roughly ten observations per indicator on the most complex construct.

Measurement Scales and Questionnaire Constructs

All constructs should be measured using multi-item, seven-point Likert scales, adapted from existing validated instruments rather than newly created items where possible. AI Capability could draw on existing IT capability scales adapted to reference AI systems specifically. Organizational Agility could draw on existing agility scales measuring sensing and response speed. Human-AI Collaboration would require a newly developed scale distinguishing augmentation items from automation items, given the absence of a widely validated instrument for this specific construct at the time of writing. Leadership Capability could adapt existing digital leadership scales. Employee Empowerment could draw on established psychological empowerment scales. Organizational Learning could draw on existing single-loop and double-loop learning scales. Innovation Performance and Organizational Performance could draw on established multi-item performance scales combining self-reported and, where available, archival financial indicators.

Reliability and Validity

Internal consistency should be assessed using Cronbach's alpha and composite reliability, with thresholds of 0.70 or above. Convergent validity should be assessed using average variance extracted, with a threshold of 0.50 or above. Discriminant validity should be assessed using the heterotrait-monotrait ratio rather than the Fornell-Larcker criterion alone, given known limitations of the latter in PLS-SEM applications. Common method bias should be assessed using Harman's single-factor test as a preliminary check, supplemented by a full collinearity test given the known limitations of Harman's test on its own.

Data Analysis Techniques

Partial least squares structural equation modeling (PLS-SEM) is proposed as the primary analysis technique, given the model's combination of formative and reflective constructs, its inclusion of a moderating relationship, and the exploratory nature of the Human-AI Collaboration construct, which lacks an extensively validated prior measurement history. Moderation should be tested using the two-stage approach recommended in the PLS-SEM literature. Mediation, particularly the Organizational Learning to Innovation Performance to Organizational Performance path, should be tested using bootstrapped indirect effects.

Ethical Considerations

The proposed study would require informed consent from all respondents, anonymization of individual and organizational identifying information in reported results, and institutional ethics review prior to data collection. Given that some questionnaire items concern employee perceptions of algorithmic oversight, particular care should be taken to ensure respondents can complete the survey without fear that individual responses could be traced back to them by their employer, since this concern could itself bias responses on the Employee Empowerment and trust-related items.

EXPECTED FINDINGS

Based on the theoretical reasoning developed above, several patterns are expected, though these remain propositions pending empirical validation rather than confirmed findings. AI Capability is expected to show a stronger direct relationship with Organizational Agility than with Organizational Performance directly, consistent with the framework's positioning of Agility as a more proximate outcome. The moderating role of Leadership Capability on the Human-AI Collaboration to Employee Empowerment relationship is expected to be one of the framework's more consequential findings if supported, since it would indicate that the same AI deployment can produce divergent employee outcomes depending on leadership practice rather than technology design alone. Organizations pursuing both augmentation and automation deliberately, rather than one to the exclusion of the other, are expected to show stronger performance outcomes, consistent with Raisch and Krakowski's (2021) paradox framing, though this proposition is among the more novel and least tested in the existing literature and should be treated with corresponding caution.

MANAGERIAL IMPLICATIONS

For practicing managers, the framework suggests that AI adoption decisions should not be evaluated solely on technical capability or cost efficiency. Decisions about where to apply decision automation versus decision augmentation carry consequences for employee trust and organizational learning capacity that extend beyond the immediate task being automated or augmented. Managers responsible for AI deployment should treat transparency and recourse mechanisms as design requirements rather than optional additions, given the algorithmic management literature's finding that these factors shape whether employees experience AI oversight as supportive or restrictive. Leadership development programs in AI-enabled organizations should place explicit weight on judgment under ambiguity and trust-building competencies, since these appear to retain or gain value as routine managerial tasks shift toward automation, rather than assuming that leadership development can proceed unchanged from pre-AI models.

POLICY IMPLICATIONS

For policy makers concerned with labor market and organizational governance questions, the framework suggests that regulatory attention to AI in workplace management should extend beyond questions of algorithmic bias in individual decisions to questions of organizational design, including whether employees have meaningful recourse when algorithmic decisions affect their work conditions. Policies encouraging transparency requirements for workplace AI systems, such as disclosure of the factors used in algorithmic scheduling or evaluation, would align with the paper's finding that transparency mediates trust outcomes. Given the underdeveloped state of digital leadership research relative to structural and algorithmic management research, policy makers supporting management education and workforce development should consider funding research specifically addressing leadership competency requirements under AI-enabled conditions, an area this paper identifies as comparatively underexamined.

PRACTICAL RECOMMENDATIONS

Organizations beginning or expanding AI adoption should consider several practical steps consistent with the framework developed here. First, organizations should map which decisions within a given process are candidates for automation, which are candidates for augmentation, and which should remain fully human, rather than applying a single approach uniformly across a business function. Second, organizations should build explanation and appeal mechanisms into algorithmic management systems before deployment rather than adding them reactively after employee concerns arise. Third, leadership development should be revised to include explicit training in managing under conditions of algorithmic oversight, including how to communicate the rationale behind AI-assisted decisions to affected employees. Fourth, organizations should treat AI adoption as an occasion for double-loop learning, revisiting the underlying assumptions behind existing workflows rather than simply inserting AI tools into unchanged processes.

LIMITATIONS

This paper is conceptual and does not report primary empirical data, so the propositions developed here require testing before they can be treated as established findings. The literature review draws on a bounded set of sources selected for relevance to the framework's constructs and theoretical foundations, and does not constitute an exhaustive systematic review of the AI and organizational design literature, which spans a wide range of disciplines including information systems, sociology, and labor economics that this paper engages only partially. The Human-AI Collaboration construct in particular lacks an extensively validated measurement history, which introduces measurement risk for any future empirical application of the proposed methodology. The framework's applicability may vary across industries and organizational sizes in ways this paper does not address, since the theoretical foundations drawn upon here were developed primarily with reference to established firms rather than early-stage or very small organizations.

FUTURE RESEARCH DIRECTIONS

Future research should prioritize empirical testing of the propositions developed in this paper, beginning with the moderating role of Leadership Capability on the relationship between Human-AI Collaboration and Employee Empowerment, given its practical significance for management practice. Development and validation of a dedicated Human-AI Collaboration measurement scale distinguishing augmentation from automation would support this and related research. Comparative research examining centralized versus decentralized AI governance structures across organizations of different sizes and industries would help clarify the boundary conditions suggested by Contingency Theory but not resolved within this paper. Longitudinal research would help address a limitation of the cross-sectional design proposed here, since organizational learning and agility are inherently processes unfolding over time rather than states fully captured at a single point of measurement. Research connecting this paper's framework to the broader hybrid work literature, examining whether AI-enabled organizational design interacts with location-based flexibility policies, would also help bridge the two research streams this paper identifies as having developed largely in parallel.

CONCLUSION

This paper has argued that artificial intelligence is reshaping organizations along dimensions that the hybrid work literature was not designed to address, including decision authority, leadership competency requirements, and the governance of algorithmic systems. Drawing on Dynamic Capabilities Theory, the Resource-Based View, Knowledge-Based View, Sociotechnical Systems Theory, Organizational Learning Theory, Contingency Theory, and Human Capital Theory, the paper developed a conceptual framework linking AI Capability to Organizational Performance through parallel structural and human-centered paths, with Leadership Capability positioned as a moderating influence on employee outcomes. The distinction between decision augmentation and decision automation, developed most explicitly by Raisch and Krakowski (2021), served as an organizing concept throughout the paper, connecting questions of organizational structure to questions of employee trust and engagement. Because the paper is conceptual, its propositions await empirical testing, and the methodology proposed here is offered as a starting point for that testing rather than a completed study. The central claim advanced in this paper is that high-performing organizations in the age of AI will be distinguished less by the sophistication of the AI systems they adopt than by how deliberately they redesign structure, leadership practice, and governance around those systems.

REFERENCES

Argyris, C., & Schön, D. A. (1978). *Organizational learning: A theory of action perspective*. Addison-Wesley.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, 3, 349-375.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109-122.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1), 366-410.

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, 44(6), 1425-1452.

Parker, S. K., & Grote, G. (2022). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, 71(4), 1171-1204.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192-210.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations*, 4(1), 3-38.

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, 4(4), 404-409.