RESEARCH AND REVIEWS IN ECONOMICS AND MANAGEMENT

Research Article

Volume 2 | issue 5

Dynamic Managerial Capabilities in High-Velocity Environments: The Intersection of Strategic Leadership and Agentic AI

Vincent English FRSA & Brian Kenny FRSA

Longford International College and University Uninettuno,Ireland.

[*]**Corresponding Author:** Vincent English FRSA, Longford International College and University Uninettuno, Ireland.

Submitted: 09 September 2026 **Accepted:** 16 September 2026 **Published:** 23 September 2026

Citation: English, V., & Kenny, B. (2026).Dynamic Managerial Capabilities in High-Velocity Environments: The Intersection of Strategic Leadership and Agentic AI. J of Research and Reviews in Economics and Management. 2(5), 01-13.

Abstract

The contemporary business environment is defined by unprecedented levels of volatility, uncertainty, complexity, and ambiguity (VUCA), rendering traditional static resource-based strategies insufficient for sustaining competitive advantage. Concurrently, the rapid advancement of agentic artificial intelligence (AI) has introduced profound questions regarding the automation of managerial oversight and the potential obsolescence of the human "micromanager". This paper provides a comprehensive theoretical synthesis of the dynamic managerial capabilities (DMC) literature, examining how strategic leaders utilise cognitive, social, and human capital to navigate uncertainty and disruption. We extend this discourse by critically integrating recent research on agentic AI, exploring whether algorithmic systems can supplant human managers in the core DMC processes of sensing, seizing, and reconfiguring. Through an analysis of current AI capabilities, organisational psychology, and strategic management theory, this investigation reveals that while agentic AI offers superior continuous monitoring, compliance enforcement, and data-driven analytics, it cannot replicate the nuanced interpersonal, normative, and moral dimensions of effective leadership. Furthermore, algorithmic supervision risks exacerbating the psychological harms associated with traditional micromanagement by fostering environments of perpetual scrutiny and diminished autonomy. Drawing on empirical findings from and among others, we propose a comprehensive conceptual framework illustrating that effective disruption management requires a hybrid human-AI architecture. In this model, AI augments the sensing and seizing processes through administrative automation, while human leaders provide the emotional labour, ethical judgment, and visionary orchestration necessary for successful organisational reconfiguration. The paper concludes with a five-phase implementation roadmap for ethical AI deployment and directions for future research [1-4].

Keywords: Dynamic Managerial Capabilities, Agentic AI, Micromanagement, High-Velocity Environments, Strategic Leadership, Organisational Learning, Sensing, Seizing, Reconfiguring, Algorithmic Supervision, Hybrid Architectures, Organisational Ambidexterity.

Introduction

The accelerating pace of technological change, the globalisation of markets, and the emergence of disruptive business models have fundamentally altered the competitive landscape for organisations across all sectors. In this high-velocity environment, characterised by rapid, discontinuous, and often unpredictable change, the ability of firms to adapt and innovate is no longer a source of temporary advantage but a prerequisite for survival [5]. The traditional resource-based view (RBV) of the firm, which posits that sustained competitive advantage derives from the possession of valuable, rare, inimitable, and non-substitutable (VRIN) resources, is increasingly recognised as insufficient in dynamic contexts [6, 7]. Resources that are valuable today may become obsolete tomorrow, and the ability to reconfigure them is what ultimately determines long-term organisational performance.

This recognition has given rise to the dynamic capabilities' framework, most comprehensively articulated by, and subsequently elaborated by [8-10]. Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. At the micro-level, Dynamic Managerial Capabilities (DMCs), introduced by, explain how individual leaders create, extend, and modify the ways in which firms make a living through the deployment of human, social, and cognitive capital

[11, 12]. The quality of these managerial capabilities directly influences the quality of strategic decisions, and ultimately the organisational performance under conditions of disruption.

However, a new paradigm is emerging that threatens to disrupt the very nature of managerial work itself: the advent of agentic artificial intelligence. As AI systems evolve from passive tools into autonomous agents capable of perceiving environments, reasoning, and acting within defined parameters, scholars and practitioners are increasingly interrogating whether these systems might assume the surveillance, co-ordination, and decision-making functions traditionally performed by human supervisors[13]. This raises a critical and timely question: Can agentic AI replace the human manager, specifically the controlling "micromanager", in executing the core DMC processes of sensing, seizing, and reconfiguring?

Micromanagement, characterised by excessive oversight, restrictive control, and diminished employee autonomy, has long been identified as detrimental to organisational health [14, 15]. Contemporary management literature consistently associates micromanagement with adverse outcomes including lower job satisfaction, decreased intrinsic motivation, and elevated staff attrition rates [16, 17]. The prospect of replacing the human micromanager with an algorithmic system therefore carries a seductive logic: remove the subjective, emotionally variable, and cognitively limited human overseer, and replace them with a consistent, tireless, and data-driven AI agent. Yet this logic, as this paper argues, is fundamentally flawed. It conflates the transactional mechanics of supervision with the transformational essence of leadership, and risks replacing one form of control with a more pervasive and psychologically damaging one.

This paper addresses three central questions. First, how do the micro-foundations of human DMCs compare to the capabilities of agentic AI in sensing disruption? Second, what are the psychological and strategic implications of using algorithmic systems to seize opportunities and enforce compliance, compared to human micromanagement? Third, how can organisations design hybrid human-AI architectures to successfully reconfigure assets while preserving workplace dignity and employee well-being? In addressing these questions, the paper integrates perspectives from strategic leadership, organisational learning, disruptive innovation theory, self-determination theory, and the emerging literature on algorithmic management to construct a holistic understanding of effective leadership in the AI era.

The paper is structured as follows. Section 2 reviews the theoretical foundations of DMCs and defines agentic AI and micromanagement. Section 3 examines the sensing capability, contrasting human cognition with algorithmic monitoring. Section 4 analyses the seizing capability, exploring the psychological costs of algorithmic surveillance versus autonomy-supportive leadership. Section 5 explores the reconfiguring capability and the necessity of hybrid architectures. Section 6 discusses enabling and constraining factors, including ethical frameworks and cognitive biases. Section 7 presents an updated conceptual framework. Section 8 discusses the theoretical implications and provides a practical implementation roadmap, and Section 9 concludes the paper.

Theoretical Foundations

From the Resource-Based View to Dynamic Capabilities

The intellectual heritage of the dynamic capabilities framework lies in the resource-based view (RBV) of the firm, which emerged as a dominant paradigm in strategic management in the 1980s and 1990s. Argued that sustained competitive advantage arises from resources that are valuable, rare, imperfectly imitable, and non-substitutable. This perspective shifted the analytical focus from the external environment to the internal resources and capabilities of the firm, emphasising the importance of idiosyncratic firm-level factors in explaining performance heterogeneity [6].

However, critics of the RBV noted its essentially static nature. In dynamic, high-velocity environments, the value of resources is transient, and the ability to reconfigure them becomes paramount[10]. Addressed this limitation by introducing the dynamic capabilities framework, positing that competitive advantage in such environments derives not from the resources themselves, but from the organisational processes, positions, and paths that enable firms to deploy and reconfigure those resources effectively. further extended the concept by proposing a hierarchical model distinguishing between incremental, renewing, and regenerative capabilities, reflecting the varying depth and scope of capability renewal. This hierarchical view is consistent with distinction between zero-level (operational), first-order (dynamic), and second-order (learning) capabilities, which provides a useful scaffold for understanding the relationship between dynamic capabilities and organisational learning [7-18].

Teece's (2007) Sensing-Seizing-Reconfiguring Framework

The most influential articulation of dynamic capabilities is framework, which disaggregates the construct into three distinct but interrelated clusters of activities. Sensing refers to the identification and assessment of opportunities and threats in the external environment: "very much a scanning, creation, learning and interpretive activity". Seizing refers to the mobilisation of resources to address sensed opportunities, requiring timely, market-oriented decisions, and the overcoming of organisational inertia. Reconfiguring refers to the continuous renewal of the organisation's resource base to maintain evolutionary fitness, explicitly requiring the escape from unfavourable path dependencies[9]. Offer a complementary perspective, defining dynamic capabilities as "the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die" (p. 1107). Their critical contribution is the distinction between dynamic capabilities in moderately dynamic markets, where they tend to be complex and analytical, and those in high-velocity markets, where they are characterised by simple rules and real-time knowledge creation. This distinction has profound implications for the role of AI: in high-velocity markets, the cognitive demands on managers are qualitatively different, requiring speed and adaptive judgment over deliberative analysis [10].

Dynamic Managerial Capabilities: Micro-foundations

Introduced DMCs to explain the heterogeneity in managerial decisions and firm performance that firm-level factors alone cannot account for [11]. They proposed that DMCs are rooted in three underlying factors: managerial human capital (knowledge, skills, and experience), managerial social capital (internal and external networks), and managerial cognition (mental models, beliefs, and interpretive frameworks). subsequently introduced the concept of "managerial cognitive capability", arguing that capabilities involve the capacity to perform not only physical but also mental activities, and that cognitive heterogeneity among top executives contributes to differential organisational performance under conditions of change. extended this framework by proposing political capital as a fourth underpinning, reflecting the importance of navigating internal organisational politics and external stakeholder relationships in the implementation of strategic change [19, 20].

Defining Agentic AI and Micromanagement

To understand how technology intersects with DMCs, we must clearly define the emerging technological capabilities and the managerial pathology they are proposed to address. Agentic AI refers to artificial intelligence systems exhibiting goal-directed behaviour without continuous human intervention. Unlike traditional automation restricted to predefined scripts, agentic systems demonstrate adaptability, contextual reasoning, and decision-making autonomy within operational boundaries[13]. Key characteristics include the perception of environmental states, the formulation of action plans, the execution of tasks, and learning from outcomes. The trajectory of AI development towards genuine agentic capacity, the ability to perceive, reason, and act autonomously, has opened a new frontier in the automation of cognitive and supervisory work. Current agentic AI systems exhibit several competencies directly relevant to supervisory functions: continuous monitoring and analytics, automated feedback generation, compliance enforcement, and multi-agent resource co-ordination. These capabilities position agentic AI as a plausible, if partial, substitute for certain managerial functions.

Micromanagement, conversely, represents a management style wherein supervisors maintain excessive control over subordinate work processes. Classic indicators include constant status monitoring, prescriptive instruction on methodology, approval requirements for routine decisions, and minimal delegation of authority [14, 15]. While sometimes motivated by quality assurance concerns, research consistently demonstrates that sustained micromanagement undermines employee autonomy, a core psychological need linked to motivation and well-being according to self-determination theory [21]. Demonstrated that employee satisfaction, a direct casualty of micromanagement, is positively associated with long-term stock returns, suggesting that the costs of micromanagement extend well beyond individual well-being to affect the firm's financial performance. The intersection of these two concepts, agentic AI and micromanagement, forms the crux of the contemporary managerial challenge: as AI becomes capable of perfect, continuous monitoring, does it alleviate the burden of the human micromanager, or does it institutionalise micromanagement at an algorithmic scale? The answer to this question has profound implications not only for organisational performance but for the dignity of labour in an increasingly automated economy [16].

Sensing: Identifying Disruption in the Age of AI
Human Cognition vs. Algorithmic Monitoring

In high-velocity environments, the ability to sense disruption before it becomes existential is perhaps the most critical DMC. Sensing involves the continuous scanning of the external environment for technological, market, and competitive signals, as well as the internal interpretation and meaning-making processes that transform raw data into actionable intelligence [9]. Describe this as the capacity to identify "weak signals" early, ambiguous indicators of change that, if correctly interpreted, can provide a significant first-mover advantage [22].

Agentic AI systems exhibit extraordinary competencies directly relevant to this supervisory function. AI platforms can process vast quantities of workflow data in real-time, identifying bottlenecks, measuring productivity metrics, and detecting anomalies that might elude human observation. Project management AI tools already integrate time-tracking, deliverable verification, and milestone validation across distributed teams [23]. In the domain of workflow monitoring, a human micromanager is limited in scope, prone to fatigue, and subject to subjective assessment. In contrast, an agentic AI system provides continuous, comprehensive, and objective metrics collection. Machine learning algorithms can also analyse communication patterns, output quality, and temporal performance trends to generate automated feedback, operating with consistent application of predefined criteria in ways that human managers, subject to cognitive biases and emotional variability, cannot.

The Human Imperative: Tacit Knowledge and Moral Judgment

Despite the superior data-processing capabilities of AI, the sensing capability remains deeply rooted in human managerial cognition. Leaders who possess rich and diverse mental models are better equipped to notice anomalies and interpret them as meaningful strategic signals rather than mere statistical noise. Found that high-construal managers engage in more expansive environmental scanning because their mental horizons encompass broader alternatives. Crucially, this relationship is moderated by cross-unit interdependence: when managers operate in highly interdependent environments, their high-level construals lead to richer alternative generation and enhanced scanning. This underscores that sensing is an interactive process reliant on both individual cognitive styles and the structural design of the organisation, a nuance that AI systems, trained on historical data, cannot replicate [3].

Furthermore, effective sensing requires the interpretation of tacit knowledge, cultural nuance, and situational factors resistant to formalisation. AI systems trained on historical data perpetuate past patterns and struggle with novel, unprecedented circumstances demanding creative responses. As observed, moral leaders use cognitive capabilities such as attention and perception to sense opportunities in turbulent environments, suggesting that the ethical and cognitive dimensions of leadership are closely intertwined. Leaders guided by strong moral principles may be more willing to act on weak signals that challenge the status quo, even when doing so involves significant personal and organisational risk. Managerial decision-making inherently incorporates evaluative judgments pertaining to distributive justice, human flourishing, and moral propriety, functions that algorithmic entities lacking consciousness and genuine affective capacity, cannot authentically replicate [24].

Found, in a longitudinal study spanning a quarter of a century, that first-mover firms were more effective at sensing and transforming under uncertainty, while follower firms delayed action due to a lack of senior management priority. This finding underscores the importance of leadership commitment to the sensing process and suggests that the failure to sense disruption is often not a failure of information but a failure of managerial attention and priority, a problem that AI can exacerbate if it lulls senior leaders into a false sense of comprehensive environmental awareness [25].

Organisational Learning and Sensing

Sensing is not solely an individual cognitive activity; it is also an organisational process dependent on the firm's learning infrastructure. Demonstrated empirically that exploratory learning, the search for novel knowledge in unfamiliar domains, is a significant antecedent of sensing capability. In their study, exploratory learning significantly predicted sensing capability in production departments ($\beta = .179$, $p < .05$), while exploitative learning predicted sensing in marketing departments ($\beta = .320$, $p < .01$). These findings suggest that the type of learning that best supports sensing is context-dependent, and that organisations must cultivate both forms of learning to develop robust sensing capabilities across their operations [1].

While AI can optimise exploitative learning by refining existing processes and identifying patterns in historical data, exploratory learning requires human curiosity, experimentation, and the willingness to challenge the status quo. Leaders play a critical role in creating the conditions for effective sensing by fostering a culture of psychological safety where weak signals can be debated without fear of algorithmic penalisation. The design of organisational structures that facilitate the flow of information from the periphery to the centre is, therefore, an important enabler of the sensing capability, a design challenge that requires human judgment, not algorithmic optimisation.

Cognitive and Algorithmic Biases as Barriers to Sensing

A critical challenge in the sensing process is the susceptibility of managers to cognitive biases that distort their perception of the environment. Examined confirmation bias as a boundary condition for DMCs, arguing that it can negatively impact the sensing, seizing, and reconfiguring processes by causing managers to selectively attend to information that confirms their existing beliefs[26]. Nickerson (1998, p. 175) defined confirmation bias as "the seeking or interpreting of evidence in ways that are partial to existing beliefs, expectations, or a hypothesis in hand." In high-velocity environments, where the signals of disruption are often weak and ambiguous, confirmation bias can be particularly damaging, leading managers to dismiss early warning signs as irrelevant noise. Managers with deeply entrenched mental models of their industry may be especially vulnerable, as their prior success reinforces the very cognitive structures that blind them to discontinuous change in their foundational upper echelons theory, argued that organisational outcomes are partially predicted by the psychological characteristics of top managers, including their cognitive frames, values, and experiences [27]. This perspective implies that the sensing capability of an organisation is to a significant degree, a function of the cognitive diversity and flexibility of its top management team. Firms with homogeneous top management teams are particularly vulnerable to collective blind spots and groupthink, which can impair their ability to sense novel disruptions. The composition of the top management team is therefore, a critical determinant of the firm's sensing capability, and should be carefully considered in executive succession planning.

However, replacing human managers with AI systems does not eliminate bias; it merely shifts it from an individual psychological phenomenon to a systemic, scaled algorithmic one. Current AI implementations remain highly susceptible to algorithmic bias derived from unrepresentative training data. An AI system trained predominantly on data from stable market conditions will systematically underweight signals of disruption, precisely because such signals are, by definition, underrepresented in historical datasets. Moreover, the opacity of many AI systems, their "black box" character, makes algorithmic bias far more difficult to detect and correct than human cognitive bias, which can at least be surfaced through structured dialogue and devil's advocacy processes. Hybrid architectures must therefore include mechanisms for humans to audit AI outputs and for AI to flag potential human cognitive biases, creating a system of mutual correction that is more robust than either approach alone.

Seizing: Mobilising Resources and the Threat of Algorithmic Micromanagement

The Strategic Logic of Seizing

Once an opportunity has been sensed, the challenge shifts to seizing the mobilisation of resources to address the opportunity and capture value from doing so. Seizing involves making strategic commitments under conditions of uncertainty, requiring both cognitive clarity about the nature of the opportunity and the social capital to build the organisational coalitions necessary for implementation[9]. In high-velocity environments, the speed of seizing is critical; the window of opportunity may be narrow, and the cost of delay can be prohibitive. demonstrated, in a seminal study of decision-making in high-velocity environments, that effective leaders use real-time information, multiple simultaneous alternatives, and rapid conflict resolution to make fast strategic decisions [28].

Agentic AI presents significant advantages in the mechanical aspects of seizing. Multi-agent systems can optimise the allocation of personnel, equipment, and materials based on demand forecasting and constraint analysis, co-ordinating activities across multiple teams simultaneously. Rule-based AI agents ensure adherence to procedural requirements and organisational policies with uniform application and comprehensive audit trails, vastly outperforming the inconsistent and selective enforcement typical of human micromanagers. In the domain of compliance enforcement, where a human micromanager applies rules inconsistently and selectively, an AI system applies uniform rules comprehensively. This represents a genuine improvement in organisational efficiency.

The Psychological Cost of Algorithmic Surveillance

However, the substitution of human management with AI in the seizing phase transcends functional capability, encompassing profound psychological dimensions. Self-determination theory distinguishes between controlling and autonomy-supportive motivational climates, demonstrating that perceived autonomy significantly predicts engagement, creativity, and persistence [17-21]. Crucially, autonomy-supportive behaviours, such as active listening, collaborative problem-solving, and recognition of individual circumstances, stem fundamentally from interpersonal interaction. They cannot be replicated by algorithmic systems.

Algorithmic supervision introduces unique psychological harms. Employees interacting with AI monitors report heightened feelings of surveillance and diminished trust compared with human oversight[4]. The absence of human reciprocity, the impossibility of negotiation, and the lack of contextual accommodation transform monitoring from an occasional inconvenience into perpetual scrutiny. Furthermore, algorithmic decisions lacking transparency foster perceptions of unfairness and powerlessness, potentially triggering reactance and disengagement. The comparative analysis of supervision modalities is instructive: while a human micromanager generates high social evaluation anxiety and low autonomy. An AI algorithmic monitor generates very high perceived omnipresence, very low autonomy, and introduces the risk of learned helplessness due to a transparency deficit. The hybrid model, by contrast, can yield moderate-to-high autonomy perceptions, but only when designed with clear boundaries, transparency mechanisms, and genuine human recourse.
Thus, deploying AI to execute the seizing function through rigid compliance enforcement does not eliminate micromanagement; rather, it scales and institutionalises it, potentially compounding the psychological harm and triggering workforce disengagement. The strategic question therefore shifts from mere technical feasibility to optimal architectural design: how can AI be deployed to enhance efficiency without sacrificing the human dimensions of leadership that sustain employee motivation and well-being?

Some researchers have argued that removing human supervisors from routine monitoring might paradoxically enhance autonomy by reducing social pressure and enabling a focus on substantive work rather than impression management [29]. Empirical evidence on this point remains mixed, with outcomes contingent on implementation specifics, organisational culture, and employee characteristics. However, the weight of evidence from the organisational psychology literature suggests that the conditions under which algorithmic supervision enhances rather than diminishes autonomy are narrow and demanding. They require, at a minimum, that employees understand how the AI system works, that they have meaningful recourse when they believe the system has made an error, and that the system is designed to support rather than replace human judgment. These conditions are rarely met in practice, particularly in early-stage deployments where organisations are still learning how to govern AI systems effectively.

The psychological dimensions of algorithmic management also have important implications for the seizing capability itself. Seizing requires the rapid mobilisation of human energy and commitment around a strategic opportunity. This mobilisation depends fundamentally on trust; trust in the leader's judgment, trust in the fairness of the process, and trust in the organisation's commitment to employee well-being. Algorithmic management systems that are perceived as opaque, unfair, or indifferent to individual circumstances precisely erode this trust, making it harder for leaders to build the coalitions and generate the discretionary effort required for effective seizing. The paradox is that the AI systems deployed to enhance the efficiency of seizing may, if poorly designed, undermine the social capital that makes seizing possible.

Corporate Control Style and AI Integration

The integration of AI into the seizing process is heavily mediated by the firm's corporate control style (CCS). Found that a rigid financial CCS, which prioritises strict ROI appraisals, can restrict a business unit's ability to seize opportunities in a timely manner. High-technology product investments, which consist of interdependent components across multiple SBUs, are difficult to quantify within standard ROI routines. Consequently, a CCS focused heavily on optimisation over flexibility may penalise risk and uncertainty, fundamentally hindering the seizing capability. If agentic AI is deployed within a highly controlling CCS, it is likely to be used purely for cost-reduction and surveillance, stifling the very agility the dynamic capabilities framework seeks to promote. Conversely, in a more strategic, decentralised CCS, AI can be utilised to empower frontline workers with real-time data, enabling them to seize local opportunities autonomously [2].

Also found that the sensing-seizing-reconfiguring triad does not necessarily occur in a fixed sequential order [2]. In cases involving technological or regulatory change, a company may need to transform in order to seize. This non-linearity has important implications for AI deployment: algorithmic systems designed around a linear sequential model of managerial decision-making will fail to capture the iterative, emergent nature of strategic adaptation in high-velocity environments.

The Challenge of Seizing Disruptive Innovations

A particular challenge in the seizing of opportunities arises in the context of disruptive innovation. Theory of disruptive innovation describes a process whereby new entrants with simpler, cheaper products initially target low-end or new market segments before progressively moving upmarket, eventually displacing incumbent firms. Incumbent firms often fail to seize disruptive opportunities because their existing business models, customer relationships, and resource allocation processes are optimised for sustaining innovations [30]. Argued that disruptive innovation requires an iterative process of sensing opportunities, seizing them through strategy deployment, and transforming organisational assets to achieve competitive advantage in volatile environments. This iterative process demands a high degree of managerial agility and the willingness to experiment with new business models, even at the risk of cannibalising existing revenue streams. Leaders who are cognitively committed to existing business models, a phenomenon Christensen described as the "innovator's dilemma", are particularly vulnerable to this failure mode. An AI system trained on the data of existing business models will systematically reinforce this dilemma, making the human capacity for creative disruption of existing mental models all the more essential[31].

Reconfiguring: Orchestrating Transformation via Hybrid Architectures

The Imperative of Reconfiguration

Reconfiguration is the most complex and demanding of the three DMC processes. It involves the restructuring of the organisation's resource base; its assets, routines, structures, and culture to maintain evolutionary fitness in the face of environmental change[9]. Unlike sensing and seizing, which can be partially automated, reconfiguration requires the physical and social transformation of the organisation, involving the creation of new routines, the dismantling of old ones, and the redeployment of assets across different activities and markets. The complexity of reconfiguration is compounded by the fact that it must often be undertaken while the organisation continues to operate its existing businesses, creating a dual challenge of managing change and maintaining operational continuity.

Found in a study of 228 large organisations, that sensing, seizing, and reconfiguring capabilities significantly impact performance, and that the timing and frequency of their deployment are crucial. Firms that reconfigure too infrequently risk becoming locked into obsolete routines and resource configurations, while those that reconfigure too frequently may incur excessive transition costs. The optimal frequency of reconfiguration is therefore, a function of the rate of environmental change and the firm's capacity to manage the costs of transformation, a judgment that requires human wisdom, not algorithmic optimisation [32].

Organisational Ambidexterity and Hybrid Human-AI Models

A central challenge in the reconfiguration process is the tension between exploitation and exploration between the need to maintain operational efficiency in existing businesses and the need to develop new capabilities and business models for the future. proposed organisational ambidexterity as the solution to this tension, defining it as the ability to simultaneously explore new opportunities while exploiting existing competencies. They identified five conditions necessary for successful ambidexterity: a compelling strategic intent justifying both exploration and exploitation; a common vision and values providing shared identity; a senior team that explicitly owns the ambidextrous strategy with common-fate rewards; separate but aligned organisational architectures for exploratory and exploitative units; and the ability of senior leadership to tolerate and resolve the tensions arising from separate alignments [33].

In the context of agentic AI, the hybrid architecture represents a new form of organisational ambidexterity. Rather than wholesale replacement of managers, deploying AI for routine monitoring, compliance, and analytics (exploitation) while retaining human managers for relationship-building, conflict resolution, and developmental coaching (exploration) appears optimal [23]. This configuration leverages technological efficiency while preserving the essential human elements of leadership. The AI system handles the exploitative, efficiency-oriented tasks that are susceptible to micromanagement, while human leaders focus on the exploratory, transformational tasks that require emotional intelligence, moral judgment, and creative vision.

Leadership, Emotional Labour, and Overcoming Path Dependencies

The reconfiguration process places particularly high demands on strategic leadership. Leaders must not only identify the need for change and design the new organisational configuration but also manage the human and political dimensions of transformation by overcoming resistance, building coalitions, and communicating a compelling vision for the future[24]. Management encompasses not merely task co-ordination, but the exercise of legitimate authority grounded in institutional roles, professional expertise, and interpersonal relationships. AI systems possess no inherent normative authority, deriving any influence solely from delegated organisational power.

Furthermore, leadership demands emotional labour that recognises distress, provides encouragement, celebrates achievement, and navigates the grief associated with dismantled routines. Current AI lacks consciousness and genuine affective capacity, rendering these transformational leadership functions impossible to replicate authentically. found that dynamic capabilities of sensing, seizing, and transforming are used by top management to orchestrate strategic change, highlighting the central role of the top management team in the reconfiguration process. The composition, diversity, and cognitive characteristics of the top management team are, therefore, critical determinants of the firm's reconfiguring capability. No AI system can substitute for this human orchestration [34].

A significant barrier to effective reconfiguration is path dependency, the tendency of organisations to be constrained by their historical choices and investments[9]. AI systems, by their nature, are trained on historical data and optimise for past patterns of success. Therefore, relying too heavily on AI for strategic reconfiguration risks locking the organisation into existing paradigms. illustrated this challenge through case studies of R.R. Donnelley & Sons and the Gramophone Company of India Limited, demonstrating how firms must use dynamic capabilities to respond to environmental discontinuities. R.R. Donnelley successfully adapted to technological discontinuity by sensing the shift to digital printing, seizing the opportunity, and reconfiguring its resources, leading to sustained leadership in the printing industry. The Gramophone Company of India Limited, by contrast, failed to respond effectively to multiple discontinuities due to a lack of sensing and seizing capabilities, leading to challenges in sustaining its relevance. Both cases highlight the importance of recognising the limits of existing capabilities and the willingness to invest in new ones, even at the cost of short-term efficiency [35].

Human leaders, possessing the cognitive flexibility to challenge dominant logics and the political capital to dismantle entrenched power structures, remain indispensable for overcoming path dependencies and driving genuine strategic renewal. The ability to challenge the dominant logic of an organisation, the shared mental models and assumptions that guide strategic decision-making, is a fundamentally human capability that requires both cognitive courage and relational trust. Leaders who have built strong social capital within their organisations are better positioned to initiate and sustain the reconfiguration process, because they can draw on the trust and goodwill of their colleagues to overcome the inevitable resistance that accompanies significant organisational change. No AI system, however sophisticated, can substitute for this deeply human form of strategic leadership.

Enabling and Constraining Factors

Organisational Learning as an Antecedent of DMCs

The development of DMCs is not a static event but an evolutionary process driven by deliberate learning[36]. Organisational learning acts as a second-order dynamic capability that reshapes first-order operational capabilities, providing the knowledge base and cognitive flexibility required for effective sensing, seizing, and reconfiguring[18]. Demonstrated empirically that both exploratory and exploitative learning are significant antecedents of DMCs, with different types of learning being important for different DMC components. Notably, exploitative learning predicted reconfiguration across both production and marketing departments, indicating that reconfiguration relies heavily on leveraging known competencies to enact structural change. The study also found that transformational leadership moderates the relationship between exploratory learning and sensing capability: for departments with high transformational leadership, the relationship between exploratory learning and sensing capability was positive and significant, while for departments with low transformational leadership, exploratory learning was not significantly related to sensing capability at all. This finding has a direct implication for AI deployment: if AI systems are used to replace transformational leadership behaviours with algorithmic monitoring, the exploratory learning that underpins sensing capability will be systematically undermined [1].

The relationship between OL and DMCs is, however, complex and context dependent. In highly dynamic environments, the pace of change may outstrip the firm's ability to learn and adapt through deliberate processes, requiring more improvisational approaches to capability development .Found that improvisational capabilities, the ability to rapidly reconfigure resources in response to unexpected events, are more effective than deliberate dynamic capabilities in highly turbulent environments. This suggests that the optimal learning strategy for DMC development may vary with the degree of environmental turbulence, a calibration that requires human judgment. Agentic AI systems, which are fundamentally optimisation-oriented, are poorly suited to the improvisational mode of capability development that high-velocity environments often demand. They can accelerate deliberate learning by processing vast quantities of data and identifying patterns, but they cannot replicate the creative, experimental, and socially embedded processes through which organisations develop genuinely novel capabilities [37].

Strategic Leadership as a Moderator

Strategic leadership plays a critical moderating role in the relationship between OL and DMCs. demonstrated that transformational leadership strengthens the relationship between exploratory learning and sensing capabilities across both production and marketing departments. For departments with low transformational leadership, exploratory learning was not significantly related to sensing capability. However, for departments with high transformational leadership, the relationship between exploratory learning and sensing capability was positive and significant. This finding has a direct implication for AI deployment: if AI is used to replace transformational leadership behaviours with algorithmic monitoring, the exploratory learning that underpins sensing capability will be undermined [1].

Conversely, transactional leadership, which focuses on clear role definition, performance monitoring, and contingent reward, was found to have a direct, positive effect on seizing and reconfiguring capabilities. This aligns closely with the capabilities of agentic AI, suggesting that the transactional dimensions of management are the most amenable to automation. The complementarity between transformational and transactional leadership, suggests that the most effective leaders in high-velocity environments may be those who can flexibly deploy both styles, a form of leadership ambidexterity that mirrors the organisational ambidexterity required for effective DMC development.

Environmental Velocity: Surge and Lurch Events

Introduced the concepts of "surge" and "lurch" events to describe fluctuations in environmental velocity. A surge event such as a disruptive technology, a new powerful competitor, or a significant regulatory change, accelerates environmental velocity, dramatically increasing the need for strong dynamic capabilities over ordinary technical capabilities. A lurch event represents a sudden deceleration or stabilisation of the environment, where the premium shifts back towards operational efficiency and technical capabilities [2].

Agentic AI is highly effective during lurch events, where standardisation, compliance, and efficiency are paramount. The consistent, tireless, and data-driven nature of AI makes it an ideal tool for managing the operational demands of a stable environment. However, during surge events, the ambiguity and novelty of the environment demand the adaptive, creative problem-solving capacities of human managers. Failing to sense a surge event and to reconfigure DMCs may limit sustainability through reduced product differentiation. Failing to sense a lurch event may result in a growing cost base and uncompetitive market propositions [2]. Managers must therefore actively calibrate their reliance on AI versus human judgment based on their reading of environmental velocity, a meta-capability that is itself a form of sensing.

Ethical Frameworks, Transparency, and Accountability

The integration of agentic AI into managerial functions introduces severe constraining factors related to ethics and accountability. Algorithmic systems governing employment decisions require clear articulation of operating principles, decision rationales, and appeal pathways. Transparency builds trust and enables meaningful contestation of errors or unjustified outcomes[29]. Furthermore, clear attribution of responsibility for algorithmic decisions is essential. When an AI-driven management system causes harm or injustice, liability must be clearly established among developers, implementers, and senior executives. Without robust ethical governance frameworks concerning fairness, privacy, and dignity, the deployment of AI will constrain, rather than enable, organisational agility.

Any AI-enhanced management system must explicitly safeguard employee autonomy through opt-out provisions for non-critical monitoring, human review of algorithmic decisions, and participation in system design processes. Current regulatory regimes are increasingly ill-suited to address technological advances whose pace surpasses policy responsiveness, placing the burden of ethical governance squarely on organisational leaders. This represents a new and critical dimension of the managerial reconfiguring capability: the ability to design and govern AI systems in ways that are both technically effective and ethically defensible.

Comparative Capability Assessment: Human Managers vs. Agentic AI

A structured comparison of the relative capacities of human managers and agentic AI systems across key supervisory domains illuminates the asymmetrical strengths and weaknesses of each approach and provides a practical foundation for hybrid architecture design.

Table 1: Comparative Capability Assessment — Human Micromanager vs. Agentic AI System

Domain	Human Micromanager	Agentic AI System
Workflow Monitoring	Limited scope, prone to fatigue, subjective assessment	Continuous, comprehensive, objective metrics collection
Real-Time Analytics	Manual aggregation, delayed insights, sampling bias	Instantaneous processing, pattern recognition, anomaly detection
Compliance Enforcement	Inconsistent application, selective enforcement	Uniform rule application, comprehensive audit trails
Feedback Provision	Contextual understanding, emotional intelligence	Standardised criteria, potential bias in training data
Interpersonal Support	Empathy, mentorship, conflict resolution	None; purely transactional interactions
Discretionary Judgment	Nuanced interpretation, value-based decisions	Algorithmic determinism, limited to training parameters
Accountability	Clear responsibility attribution	Diffuse liability (developer, implementer, organisation)
Adaptability	Novel situation handling, creative problem-solving	Pattern-dependent, struggles with unprecedented contexts
Normative Authority	Grounded in institutional roles and relationships	Derived solely from delegated organisational power
Moral Responsibility	Can bear moral responsibility for decisions	Incapable of bearing moral responsibility

This comparison illuminates that AI excels in continuous monitoring, consistency, and data-processing tasks, while human managers retain superior capacity for relational support, ethical judgment, and adaptive response. The strategic question therefore shifts from mere technical feasibility to optimal architectural design: which supervisory functions should be automated, which should remain human-led, and how should the interface between the two be managed to preserve employee well-being and organisational agility?.

Personality as a Micro-foundation of DMCs

Proposed personality traits as a micro-foundation of DMCs, arguing that individual personality characteristics influence the capacity of managers to sense, seize, and reconfigure. Specifically, they proposed that openness to experience is positively associated with sensing capability, conscientiousness with seizing capability, and emotional stability with reconfiguring capability[38]. This perspective is consistent with the upper echelons theory, which emphasises the role of managerial psychological characteristics in shaping organisational outcomes [27]. The implication for practice is that organisations should consider personality assessment as part of their executive selection and development processes, with particular attention to the traits that are most relevant for the specific DMC demands of their environment. No AI system can replicate the dispositional openness to experience that enables a leader to genuinely sense novel disruption, or the emotional stability that enables a leader to guide an organisation through the grief and uncertainty of genuine transformation.

Conceptual Framework for Dynamic Managerial Capabilities in the AI Era

Drawing on the theoretical and empirical literature reviewed above, we propose a conceptual framework that integrates agentic AI into the DMC model. The framework depicts the relationships between the antecedents of DMCs, the three core processes, and the structural and ethical moderators introduced by AI. Crucially, it positions the Hybrid Human-AI Architecture not as an optional add-on, but as the foundational design principle that makes effective DMC exercise possible in the contemporary environment.

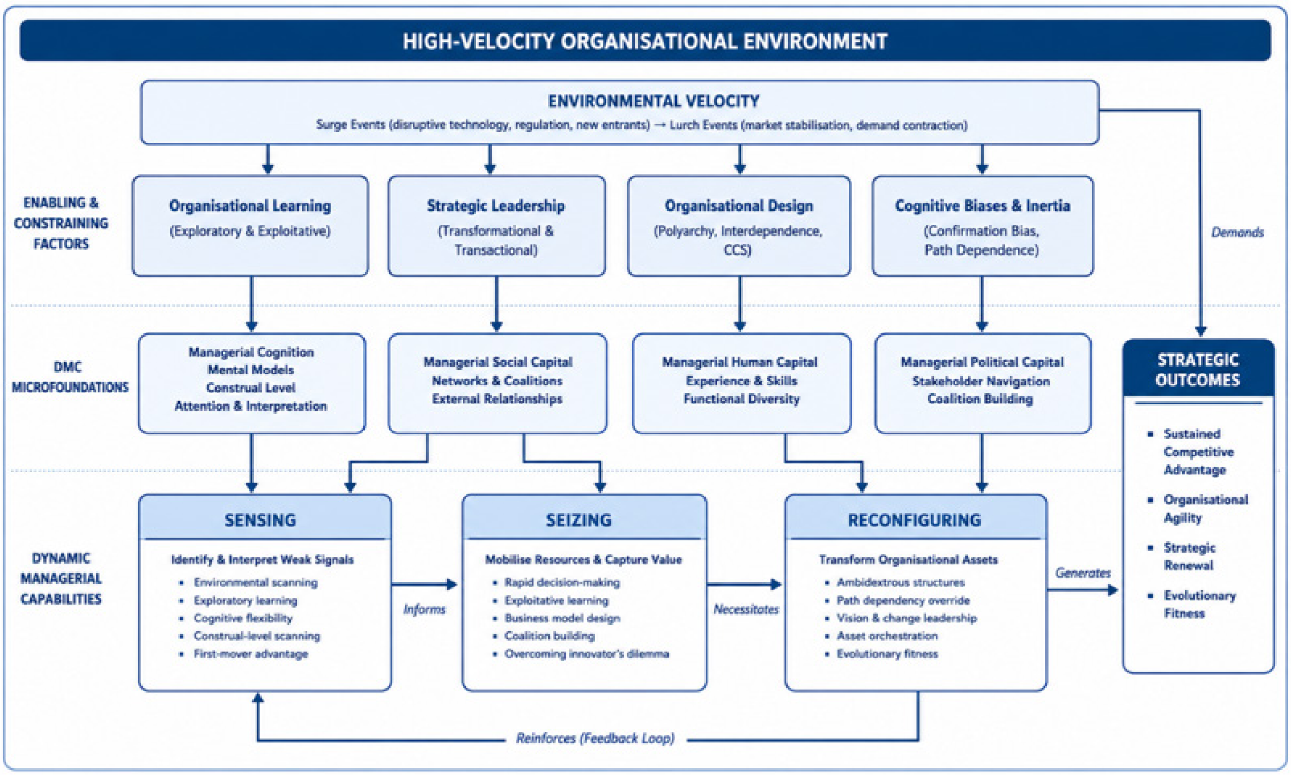

Figure 1: Conceptual Model: Dynamic Managerial Capabilities and Agentic AI in High-Velocity Organisational Environments

Figure 1 provides a visual representation of this integrated framework, showing how human managerial capabilities and agentic AI interact across the sensing, seizing, and reconfiguring dimensions of DMCs. However, the value of the model lies not only in these broad relationships, but also in the specific allocation of complementary roles between human leaders and AI systems within each capability. Table 1 therefore extends the conceptual model by disaggregating each DMC process into its principal human micro-foundation, corresponding agentic AI capability, continuing human imperative, optimal human–AI architecture, and associated boundary conditions. It also identifies the leadership styles, environmental triggers, and intended organisational outcomes most closely associated with each dimension. In this way, the table translates the visual architecture of Figure 1 into a more explicit analytical framework, clarifying both where agentic AI can augment managerial capability and where human judgement, relational competence, and normative authority remain indispensable.

Table 2: Conceptual Framework of DMCs and Agentic AI Integration

Dimension	Sensing	Seizing	Reconfiguring
Primary Human Micro-foundation	Managerial Cognition	Managerial Social Capital	Managerial Human & Political Capital

Agentic AI Capability	Continuous monitoring, anomaly detection, real-time analytics	Resource coordination, uniform compliance enforcement	Scenario modelling, data-driven forecasting, transition tracking
Human Imperative	Interpreting weak signals, moral judgment, tacit knowledge	Coalition building, emotional intelligence, contextual adaptation	Vision communication, emotional labour, overcoming path dependency
Optimal Architecture	AI flags anomalies; Human interprets strategic meaning	AI optimises allocation; Human manages interpersonal dynamics	Human leads transformation; AI tracks transition metrics
Key Boundary Condition	Confirmation bias vs. Algorithmic bias from training data	Algorithmic surveillance, learned helplessness, loss of autonomy	Path dependency (AI's reliance on historical data); normative authority deficit
Leadership Style	Transformational (moderates exploratory learning)	Transactional (direct positive effect on seizing)	Orchestrational / Ambidextrous
Environmental Trigger	Surge events demand human sensing	Lurch events amenable to AI compliance	Surge events demand human-led reconfiguration
Primary Outcome	Opportunity identification and strategic intelligence	Value capture without psychological harm	Competitive renewal and evolutionary fitness

The framework highlights several important theoretical propositions. First, the three DMC processes are not sequential but iterative and interdependent; effective sensing creates the conditions for effective seizing, which in turn creates the need for reconfiguring, which then reshapes the organisation's sensing capabilities. Second, AI capabilities and human micro-foundations are complementary, not substitutable: AI excels at the quantitative, continuous, and objective elements of management, while humans are required for the qualitative, normative, and transformational elements. Third, the effectiveness of DMCs is moderated by both individual-level factors (cognitive biases, personality) and organisational-level factors (design, culture, learning infrastructure, corporate control style, ethical frameworks). Fourth, the introduction of agentic AI creates a new set of constraining factors; algorithmic bias, transparency deficits, and accountability diffusion that must be actively managed by human leaders.

Discussion and Implementation Roadmap

Theoretical Implications

This paper makes several contributions to the theoretical literature on DMCs and dynamic capabilities more broadly. First, it bridges the DMC literature with emerging research on artificial intelligence and organisational psychology, challenging the technologically determinist view that AI can seamlessly replace human management. By applying the sensing-seizing-reconfiguring framework, we demonstrate that while AI can replicate the transactional mechanics of management (often associated with micromanagement), it cannot replicate the transformational dynamics required for genuine strategic renewal. This distinction is theoretically important because it clarifies the boundary conditions of AI's applicability in managerial contexts. Second, the paper highlights that algorithmic supervision, if implemented without human mediation, risks exacerbating the very psychological harms, loss of autonomy, increased stress, and disengagement, that the dynamic capabilities framework relies upon to foster innovation. Self-determination theory provides the psychological mechanism: when employees perceive their environment as controlling rather than autonomy-supportive, their intrinsic motivation is undermined, reducing the exploratory learning and creative problem-solving that underpin effective sensing and reconfiguring. This creates a paradox: the AI systems deployed to enhance organisational efficiency may, if poorly designed, undermine the very human capabilities that make the organisation strategically adaptive. Third, the paper extends the DMC framework by incorporating ethical governance as a new enabling and constraining factor. The deployment of agentic AI in managerial contexts is not merely a technical challenge but a normative one, requiring organisations to make explicit choices about the values they wish to embed in their management systems. This has implications for the study of corporate governance and organisational ethics, suggesting that the governance of AI systems should be treated as a strategic capability in its own right [21].

Fourth, the paper contributes to the environmental velocity literature by demonstrating that the optimal balance between AI and human management varies with the type of environmental event. During surge events, human sensing and reconfiguring capabilities are paramount; during lurch events, AI-driven efficiency and compliance are more valuable. This contingency perspective adds nuance to the existing literature on dynamic capabilities and environmental dynamism.

Practical Implications: The Implementation Roadmap

For organisations contemplating AI integration into managerial functions, we propose a phased implementation roadmap designed to mitigate risk and preserve employee agency. This roadmap draws on the strategic logic of the DMC framework and the ethical principles identified in the AI management literature.

Phase 1 — Assessment: Audit current management practices to identify automatable functions (e.g., routine compliance, basic resource allocation, performance metric collection). Conduct stakeholder consultations and impact analyses to ensure clarity of scope and employee buy-in. The goal of this phase is to distinguish between the transactional mechanics of management that are amenable to AI automation and the transformational dimensions that must remain human-led.

Phase 2 — Design: Develop a hybrid architecture that clearly defines human and AI boundaries. Establish ethical review board oversight and robust transparency protocols to ensure alignment with organisational values. Explicitly safeguard employee autonomy through opt-out provisions for non-critical monitoring, human review of algorithmic decisions, and participation in system design processes. The design phase should also establish clear accountability structures, specifying where liability rests when AI-driven management causes harm or injustice.

Phase 3 — Pilot: Conduct limited deployments with iterative refinement. Ensure opt-in participation and clear exit provisions. Measure success through employee satisfaction, psychological well-being, and productivity gains, not just cost reduction. The pilot phase should include qualitative research to understand the lived experience of employees under hybrid management, capturing psychological impacts that quantitative metrics may miss.

Phase 4 — Scale: Execute a graduated expansion accompanied by comprehensive training for both managers and employees. Maintain continuous monitoring of employee well-being and engagement, and establish clear grievance channels for algorithmic decisions. The scaling phase should be contingent on evidence from the pilot that the hybrid architecture is achieving its intended outcomes without generating unintended psychological harms.

Phase 5 — Governance: Establish ongoing oversight and accountability mechanisms. Conduct regular audits and independent reviews to ensure compliance rates and the effectiveness of dispute resolution. The governance phase should also include mechanisms to update the AI system as the environment changes, ensuring that the AI's sensing capabilities remain calibrated to current, rather than historical, market conditions.

Figure 2 summarises the five phases that translate the paper's theoretical argument into a practical pathway for responsible AI-enabled management. Rather than treating AI adoption as a single technological intervention, the roadmap conceptualises implementation as a cumulative process in which assessment, design, experimentation, scaling, and governance build upon one another. Each phase introduces a distinct managerial priority while preserving the framework's central principle: AI should augment, not displace, the human capabilities required for judgement, relational leadership, ethical accountability, and strategic adaptation. Figure 1 synthesises this implementation logic visually, illustrating the progression from initial organisational assessment through to continuous governance and system renewal. Importantly, the model should not be interpreted as rigidly linear; feedback from piloting, scaling, and governance may require organisations to revisit earlier design assumptions as employee responses, technological capabilities, and environmental conditions evolve.

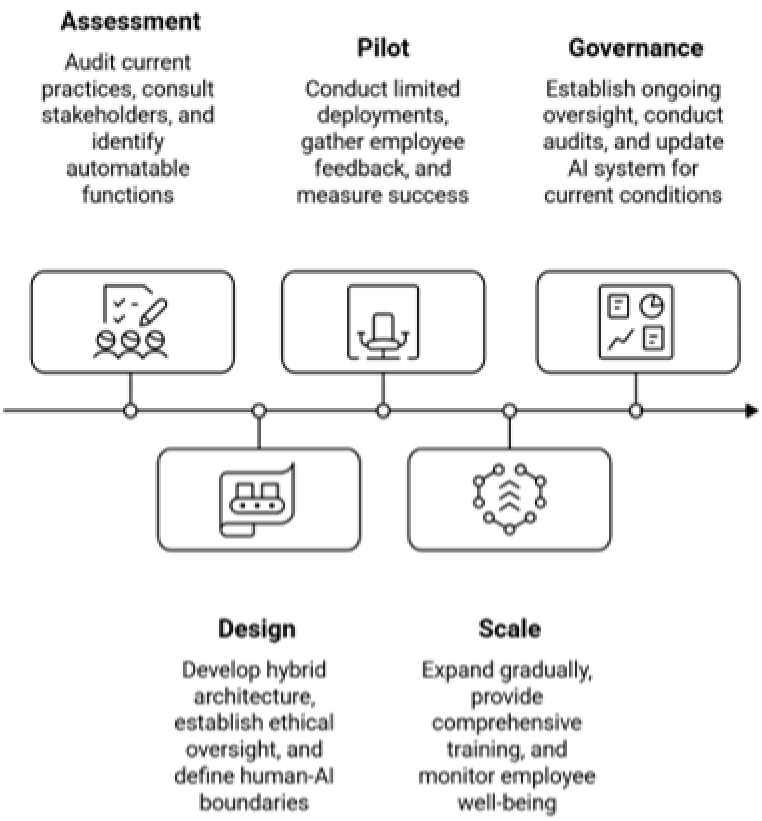

Figure 2: Five Phases of AI-Driven Management Implementation

Limitations and Future Research

This paper is primarily theoretical, relying on a synthesis of existing literature. Future research must prioritise longitudinal empirical studies examining the psychological impacts of algorithmic supervision on employee motivation, creativity, and firm-level agility. Specifically, research is needed to quantify the effectiveness of different hybrid human-AI architectures in high-velocity environments, and to identify the conditions under which AI augmentation enhances, rather than undermines, the human DMCs of sensing, seizing, and reconfiguring. The absence of large-scale empirical studies directly testing the relationship between AI deployment and DMC effectiveness represents a significant gap in the current literature, and one that is becoming increasingly urgent as organisations accelerate their adoption of agentic AI systems. Additionally, as AI capabilities continue to evolve towards artificial general intelligence, the boundary between automatable tasks and essential human leadership functions will continually shift, requiring ongoing theoretical reassessment. The trajectory described by suggests that AI systems will increasingly be capable of performing tasks that currently require human judgment, including the interpretation of ambiguous signals, the navigation of complex social dynamics, and the formulation of creative strategic responses. This trajectory raises profound questions about the long-term future of managerial work and the nature of human competitive advantage in an increasingly automated economy. Future theoretical work should engage seriously with these questions, rather than assuming that the current boundaries between human and AI capabilities are fixed [13].

Future research should also examine the cross-cultural dimensions of algorithmic management, as the psychological impacts of AI supervision may vary significantly across national cultures with different orientations towards authority, autonomy, and privacy. The Hofstedian dimensions of power distance and individualism, for example, may moderate the relationship between algorithmic supervision and employee well-being in ways that have important implications for the design of hybrid human-AI architectures in multinational organisations. Finally, the governance of AI management systems represents an important area for future research, particularly in relation to the development of regulatory frameworks that can keep pace with the rapid evolution of AI capabilities. The current regulatory vacuum in many jurisdictions creates significant risks for organisations that deploy AI management systems without adequate governance structures, and for the employees who are subject to those systems[39].

Conclusion

The proposition that agentic AI can replace the human micromanager, or indeed, any meaningful conception of management, falters upon rigorous examination. While agentic AI presents transformative potential for reshaping management practices, offering capabilities for monitoring, co-ordination, and analytics that far exceed human capacity, it lacks the interpersonal, normative, and moral dimensions that are irreducible to computational processes. In high-velocity environments, the dynamic managerial capabilities of sensing, seizing, and reconfiguring require more than data processing; they require visionary interpretation, coalition building, and the emotional labour needed to guide people through disruptive change. AI systems can process vast quantities of data in real-time, enforce compliance uniformly, and optimise resource allocation with precision. But they cannot interpret the moral significance of a weak signal, build the trust necessary for a coalition, or inspire an organisation to embrace the grief and uncertainty of genuine transformation.

Rather than pursuing wholesale replacement strategies that risk creating environments of perpetual algorithmic scrutiny, potentially compounding the psychological harms of traditional micromanagement at industrial scale, organisations must embrace hybrid augmentation approaches. By leveraging AI to reduce administrative burdens and eliminate the mechanical aspects of micromanagement, organisations can free human leaders to invest in the relational and transformational capacities that truly drive strategic renewal. The five-phase implementation roadmap proposed in this paper provides a practical pathway for achieving this balance, grounded in the ethical principles of transparency, accountability, and employee dignity. Ultimately, the future of competitive advantage in high-velocity environments lies not in choosing between human managers and artificial intelligence, but in designing ethical, hybrid architectures that harness the strengths of both. The dynamic managerial capabilities of sensing, seizing, and reconfiguring will remain fundamentally human endeavours, enriched and amplified, but never replaced, by the extraordinary analytical power of agentic AI.

References

1. Bornay-Barrachina, M., López-Cabrales, Á., Salas-Vallina, A. (2023). Sensing, seizing, and reconfiguring dynamic capabilities in innovative firms: Why does strategic leadership make a difference? BRQ Business Research Quarterly, 28(2), 399-420.
2. Garri, M. (2020). Building dynamic capabilities for high margin product development: A corporate control style perspective. Qualitative Research in Organizations and Management: An International Journal.
3. Harvey, J. (2022). Microfoundations of sensing capabilities: From managerial cognition to team behavior. Strategic Organization.
4. 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.
5. Teece, D. J., Peteraf, M., Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. California Management Review, 58(4), 13-35.
6. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.
7. Ambrosini, V., Bowman, C., Collier, N. (2009). Dynamic capabilities: An exploration of how firms renew their resource base. British Journal of Management, 20(S1), S9-S24.
8. Teece, D. J., Pisano, G., Shuen, A. (1997). Dynamic ca-

pabilities and strategic management. Strategic Management Journal, 18(7), 509-533.
9. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319-1350.
10. Eisenhardt, K. M., Martin, J. A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, 21(10-11), 1105-1121.
11. Adner, R., Helfat, C. E. (2003). Corporate effects and dynamic managerial capabilities. Strategic Management Journal, 24(10), 1011-1025.
12. Helfat, C. E., Martin, J. A. (2015). Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. Journal of Management, 41(5), 1281-1312.
13. Bengio, Y., (2024). Pathways toward artificial general intelligence: A survey. Nature Machine Intelligence, 6(3), 234-251.
14. Kanter, R. M. (1977). Men and women of the corporation. New York: Basic Books.
15. Harter, J. K., Schmidt, F. L., Hayes, T. L. (2002). Business-unit-level relationship between employee satisfaction, employee engagement, and business outcomes. Journal of Applied Psychology, 87(2), 268-279.
16. Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. Journal of Financial Economics, 101(3), 623-644.
17. Gagné, M., Deci, E. L. (2005). Self-determination theory and work motivation. Journal of Organizational Behavior, 26(4), 331-362.
18. Winter, S. G. (2003). Understanding dynamic capabilities. Strategic Management Journal, 24(10), 991-995.
19. Helfat, C. E., Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. Strategic Management Journal, 36(6), 831-850.
20. Baishya, S., Karna, A., Mahapatra, D., Kumar, S., Mukherjee, D. (2025). Dynamic managerial capabilities: A critical synthesis and future directions. Journal of Business Research, 186, 115015.
21. Ryan, R. M., Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68-78.
22. Day, G. S., Schoemaker, P. J. H. (2016). Adapting to fast-changing markets and technologies. California Management Review, 58(4), 59-77.
23. Wilson, H. J., Daugherty, P. (2023). Collaborative intelligence: Humans and AI working together. Harvard Business Review, 101(4), 112-121.
24. Bacha, E., Niesten, E. (2024). Cognitive capabilities of moral leaders in turbulent environments: A review, theory integration and way forward. Journal of Managerial Psychology.
25. Cuthbertson, R., Paavola, L. (2024). Innovating for an uncertain future: Dynamic capabilities for seizing new market opportunities. Academy of Management Proceedings.
26. Cenophat, S., Adegbile, A. (2021). Confirmation bias: A boundary condition for dynamic managerial capabilities in the context of strategic change. Contributions to Management Science.
27. Hambrick, D. C., Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. Academy of Management Review, 9(2), 193-206.
28. Eisenhardt, K. M. (1989). Making fast strategic decisions in high-velocity environments. Academy of Management Journal, 32(3), 543-576.
29. Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, accountability, transparency, and explainability. Human–Computer Interaction, 33(5-6), 446-456.
30. Christensen, C. M. (1997). The innovator's dilemma: When new technologies cause great firms to fail. Harvard Business School Press.
31. Cruz-Sanchez, O. M., Sarmiento-Muñoz, M. H., Domínguez, O. (2020). Disruptive innovation and dynamic capabilities approach: Sensing, seizing, and transforming. Proceedings of the Academy of Management.
32. Wilden, R., Gudergan, S. (2009). The effects of sensing and seizing of market opportunities and reconfiguring activities on the organisational resource base. Proceedings of the Academy of Management.
33. O'Reilly, C. A., Tushman, M. L. (2011). Organizational ambidexterity in action: How managers explore and exploit. California Management Review, 53(4), 5-22.
34. Maijanen, P., Ritala, P. (2018). Dynamics of dynamic capabilities: Cross-level processes of sensing, seizing and transforming. Academy of Management Proceedings.
35. Darwin, C. (2011). Discontinuity in the environment, firm response, and dynamic capabilities. Vikalpa: The Journal for Decision Makers, 36(3), 13-28.
36. Zollo, M., Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. Organization Science, 13(3), 339-351.
37. Pavlou, P. A., El Sawy, O. A. (2010). The "third hand": IT-enabled competitive advantage in turbulence through improvisational capabilities. Information Systems Research, 21(3), 443-471.
38. Harrington, S., Kevill, A. (2019). Personality as a micro-foundation of dynamic managerial capabilities. Academy of Management Proceedings.
39. Felin, T., Powell, T. C. (2016). Designing organizations for dynamic capabilities. California Management Review, 58(4), 78-96.