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Who Innovates When AI Acts? Agentic Systems as Engines of Strategic Renewal

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Abstract

The rapid emergence of agentic artificial intelligence (AI) systems—AI systems capable of autonomous goal-setting, decision-making, and coordinated action—raises a fundamental strategic question: who innovates when AI acts? This article develops a conceptual framework that positions agentic systems not merely as tools for operational efficiency, but as engines of strategic renewal. We argue that as AI systems increasingly participate in sensing opportunities, recombining knowledge, and executing experimentation, innovation shifts from being solely human-driven to being co-produced within human–AI collectives. Building on theories of dynamic capabilities, organizational learning, and strategic entrepreneurship, we introduce the concept of "distributed agency in innovation," where initiative, experimentation, and adaptation are partially delegated to AI agents operating within bounded governance structures. We identify three mechanisms through which agentic systems enable strategic renewal: continuous opportunity discovery, autonomous variation and selection, and rapid capability reconfiguration. At the same time, we highlight emerging tensions related to accountability, control, and the redefinition of managerial roles. By reframing AI agents as strategic actors embedded in organizational processes, this article contributes to debates on digital transformation and innovation governance and outlines a research agenda for understanding how firms design, orchestrate, and regulate innovation in the age of agentic AI.

Keywords: Agentic AI; Artificial Intelligence; Strategic Renewal; Innovation; Dynamic Capabilities; Organizational Learning; Human–AI Collaboration; Digital Transformation; Autonomous Systems; Strategic Management

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1. Introduction

Artificial intelligence (AI) has rapidly evolved from a back-end analytical tool to a central driver of organizational transformation. Early applications of AI in firms focused primarily on automation, prediction, and process optimization (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018). However, recent advances in large-scale machine learning models, reinforcement learning, and multi-agent architectures have enabled the development of increasingly autonomous, goal-directed systems capable of planning, adapting, and interacting with complex environments. These "agentic" AI systems go beyond static decision support: they can initiate actions, generate novel solutions, coordinate with other systems, and iteratively refine strategies with minimal human intervention(Ajmal, Islam, & Khalid, 2025d). As AI systems move from tools to semi-autonomous actors embedded within organizational processes, a fundamental strategic question emerges: who innovates when AI acts?

Innovation has long been understood as a human-centered activity rooted in managerial cognition, entrepreneurial initiative, and organizational learning. Foundational theories emphasize the role of firms in integrating and recombining knowledge (Grant, 1996), orchestrating dynamic capabilities to sense and seize opportunities (Teece, Pisano, & Shuen, 1997; Teece, 2007), and cultivating entrepreneurial processes that generate strategic renewal (Agarwal & Helfat, 2009). Within these frameworks, managers and entrepreneurs are typically positioned as the primary agents of change—those who identify opportunities, allocate resources, and shape firm trajectories(Ajmal, Khalid, & Islam, 2025b).

Yet digital technologies have increasingly altered the locus of innovation. Research on digital innovation highlights how software-based technologies enable generativity, modular recombination, and distributed experimentation across ecosystems (Yoo, Henfridsson, & Lyytinen, 2010; Nambisan, Wright, & Feldman, 2019). Digital platforms blur firm boundaries and redistribute innovation agency among users, developers, and algorithmic infrastructures. More recently, scholars have begun to recognize that AI systems themselves can participate in creative and strategic processes, generating novel product designs, optimizing R&D portfolios, and autonomously adapting operational strategies (Cockburn, Henderson, & Stern, 2018). In this emerging context, AI is not merely augmenting human decision-making—it is increasingly embedded in the innovation process itself(Islam, Ajmal, & Khalid, 2025a).

The rise of agentic AI systems intensifies this shift. Unlike traditional decision-support systems, agentic systems can autonomously set sub-goals, experiment with alternatives, learn from feedback, and coordinate actions across tasks. This capability aligns closely with the microfoundations of dynamic capabilities, which emphasize sensing, seizing, and transforming as core processes of strategic renewal (Teece, 2007). When AI systems conduct continuous environmental scanning, simulate alternative strategic scenarios, and autonomously test product variations, they effectively perform functions historically attributed to managers and entrepreneurial teams. As such, the boundaries of agency in innovation become blurred(Islam, Ajmal, & Khalid, 2025b).

At the same time, the delegation of initiative to AI raises profound governance and accountability challenges. Algorithmic decision-making can produce opaque outcomes, embed biases, and create new forms of organizational risk (Pasquale, 2015; Binns, 2018). Moreover, as AI systems gain autonomy, questions emerge regarding responsibility for strategic choices, ethical oversight, and the alignment of AI-generated actions with organizational purpose (Raisch & Krakowski, 2021). Rather than eliminating human roles, the rise of agentic AI reconfigures them—shifting managerial work toward oversight, orchestration, and the design of human–AI collaboration architectures(Islam, Ajmal, & Khalid, 2025c).

Despite growing attention to AI and strategy, the literature has largely focused on performance implications, productivity gains, and complementarities between human and machine intelligence (Brynjolfsson, Rock, & Syverson, 2017; Raisch & Krakowski, 2021). Less attention has been paid to the deeper ontological shift implied by agentic systems: the redistribution of innovative agency within organizations. Who is the innovator when a machine autonomously generates and tests new product features? How should firms conceptualize strategic renewal when experimentation and adaptation are partially delegated to AI agents? And what new governance mechanisms are required when strategic initiative is distributed across human and artificial actors?

This article addresses these questions by developing a conceptual framework that positions agentic AI systems as engines of strategic renewal. Drawing on dynamic capabilities theory, organizational learning, and digital innovation research, we argue that innovation in AI-enabled organizations increasingly emerges from human–AI collectives rather than from human actors alone. We introduce the concept of distributed agency in innovation to describe a configuration in which initiative, experimentation, and adaptation are co-produced by managers, employees, and autonomous AI agents operating within bounded governance structures.

By reframing AI systems as strategic actors embedded within organizational processes, this study contributes to three streams of literature. First, it extends dynamic capabilities theory by examining how sensing, seizing, and transforming processes are partially automated and algorithmically enacted(Khalid, Islam, & Ajmal, 2025a). Second, it enriches research on digital innovation by conceptualizing AI agents as generative participants rather than infrastructural enablers. Third, it advances debates on AI governance by highlighting the strategic implications of delegating innovation agency to machines. Ultimately, understanding who innovates when AI acts is not merely a philosophical question—it is central to how organizations design structures, allocate authority, and sustain renewal in the age of intelligent, autonomous systems(Khalid, Islam, & Ajmal, 2025b).

2. Literature Review

2.1. Innovation and Strategic Renewal

Innovation has traditionally been conceptualized as a human-centered, organizationally embedded process of variation, selection, and retention (Nelson & Winter, 1982). Within strategic management, strategic renewal refers to the process through which firms refresh or transform their resource base, capabilities, and strategic orientation to maintain competitiveness over time (Agarwal & Helfat, 2009). This renewal depends on dynamic capabilities—organizational abilities to sense opportunities and threats, seize them through investment and resource mobilization, and transform the firm accordingly (Teece, Pisano, & Shuen, 1997; Teece, 2007).

Dynamic capabilities theory emphasizes managerial cognition and entrepreneurial judgment as central microfoundations of sensing and seizing activities (Helfat & Peteraf, 2015). Managers interpret signals, shape opportunity recognition, and orchestrate assets under conditions of uncertainty. Organizational learning theories similarly frame innovation as emerging from collective human processes—experimentation, feedback interpretation, and knowledge integration (Argote & Miron-Spektor, 2011). Thus, across foundational perspectives, innovation and renewal are implicitly human-driven phenomena, even when mediated by technological tools.

However, digital transformation challenges this assumption. Digital technologies enable rapid recombination of knowledge, continuous experimentation, and scalable coordination across

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ecosystems (Yoo, Henfridsson, & Lyytinen, 2010). As innovation becomes increasingly software-intensive and data-driven, the role of algorithmic systems in generating variation and shaping strategic options expands. This shift necessitates revisiting the locus of agency in strategic renewal(Khalid, Islam, & Ajmal, 2025c).

2.2. Digital Innovation and Distributed Agency

Digital innovation research highlights how digital technologies alter the nature of products, processes, and organizational boundaries (Nambisan, Wright, & Feldman, 2019). Unlike traditional physical technologies, digital artifacts are reprogrammable, generative, and layered, allowing continuous modification and recombination (Yoo et al., 2010). These properties enable distributed innovation, where value creation emerges from interactions among heterogeneous actors—firms, users, platforms, and developers.

Recent scholarship extends this perspective by recognizing algorithmic systems as active participants in organizing processes. Leonardi (2011) argues that material artifacts shape organizational action through affordances, influencing what actors can and cannot do. With AI systems, these affordances become adaptive and learning-based, meaning that the technology itself evolves over time. As AI systems generate predictions, recommendations, and increasingly autonomous decisions, they influence not only operational processes but also strategic trajectories.

Research on platform ecosystems further illustrates this distributed agency. Digital platforms structure interactions and govern innovation pathways through algorithmic rules and data-driven coordination (Tiwana, Konsynski, & Bush, 2010). In such contexts, innovation outcomes emerge from socio-technical configurations rather than isolated human decisions. However, most digital innovation literature still treats AI as infrastructure or augmentation, rather than as a semi-autonomous strategic actor.

2.3. Artificial Intelligence and Organizational Decision-Making

The integration of AI into organizational processes has been examined from both performance and governance perspectives. Brynjolfsson, Rock, and Syverson (2017) argue that AI represents a general-purpose technology whose productivity benefits depend on complementary organizational investments. Empirical studies suggest that AI adoption enhances firm performance when combined with human expertise and organizational redesign (Raisch & Krakowski, 2021).

A central theme in this literature is the automation–augmentation paradox: AI can both substitute for and complement human labor (Raisch & Krakowski, 2021). In decision-making contexts, algorithms may outperform humans in prediction tasks but require human oversight for contextual interpretation and ethical judgment. This interplay complicates traditional models of managerial authority.

Importantly, recent research highlights that AI systems increasingly contribute to knowledge generation. Cockburn, Henderson, and Stern (2018) suggest that machine learning transforms the innovation process by lowering the cost of experimentation and expanding the space of discoverable solutions. In R&D settings, AI can autonomously generate hypotheses, design experiments, and optimize product configurations. Such developments indicate that AI systems are not merely supporting innovation but actively shaping its direction.

At the same time, concerns about algorithmic opacity and accountability complicate delegation to AI systems. Pasquale (2015) describes the “black box” nature of algorithmic decision-making, which limits transparency and managerial control. Binns (2018) emphasizes that fairness and accountability require explicit governance mechanisms, particularly when algorithmic outputs influence consequential organizational decisions. As AI systems gain autonomy, governance structures must adapt to ensure alignment with organizational goals and societal norms.

2.4. Agentic Systems and the Reconfiguration of Strategic Agency

While much AI research focuses on prediction and automation, recent advances enable agentic systems capable of autonomous planning, adaptation, and multi-step task execution. These systems integrate reinforcement learning, generative models, and multi-agent coordination architectures, allowing them to set sub-goals and iteratively refine strategies. Although management research has yet to fully theorize such systems, their capabilities resonate with core dimensions of dynamic capabilities.

Teece (2007) conceptualizes dynamic capabilities as involving sensing (identifying opportunities), seizing (mobilizing resources), and transforming (reconfiguring assets). Agentic AI systems increasingly perform sensing through continuous data monitoring, seizing through automated experimentation and optimization, and transforming through real-time reconfiguration of processes. This suggests a partial automation of strategic functions traditionally attributed to managers.

Helfat and Peteraf (2015) argue that managerial cognitive capabilities underpin strategic adaptation. Yet as AI systems generate alternative scenarios, simulate outcomes, and propose strategic adjustments, the cognitive burden shifts. Managers transition from sole decision-makers to orchestrators of human–AI collectives. The locus of initiative becomes distributed across socio-technical networks rather than residing exclusively in human actors.

This distributed configuration challenges conventional theories of entrepreneurship and strategic renewal. Agarwal and Helfat (2009) frame renewal as driven by top management and entrepreneurial action. However, when AI agents autonomously generate product innovations or strategic recommendations, innovation emerges from hybrid agency. Human actors design objectives and governance parameters, while AI agents execute experimentation and adaptation within those bounds.

2.5. Toward a Theory of Distributed Innovation Agency

Synthesizing these streams reveals a critical gap: existing theories explain how humans innovate with digital tools, but they do not fully account for innovation when AI systems act autonomously. Dynamic capabilities theory provides a foundation for understanding renewal, yet it assumes human agency. Digital innovation research acknowledges distributed processes but under-theorizes AI autonomy. AI governance literature addresses accountability but focuses primarily on ethics rather than strategic transformation.

Agentic systems blur boundaries between tool and actor. They generate variation, evaluate alternatives, and enact changes in real time. As a result, innovation becomes co-produced by humans and machines operating within structured governance systems. This necessitates reconceptualizing innovation as a distributed agency process, where strategic initiative is shared across socio-technical configurations.

Understanding this shift is essential for both theory and practice. Theoretically, it expands the microfoundations of dynamic capabilities to include algorithmic actors. Practically, it informs organizational design choices regarding oversight, accountability, and capability development. As AI systems continue to evolve, clarifying their role in strategic renewal becomes central to the future of management scholarship.

3. Conceptual Framework: Agentic Systems as Engines of Strategic Renewal

3.1. Theoretical Foundation

Strategic renewal refers to the processes through which firms refresh, recombine, and transform their resource base to sustain competitive advantage over time (Agarwal & Helfat, 2009). At its core lies the dynamic capabilities framework, which conceptualizes renewal as a function of sensing opportunities and threats, seizing opportunities through investments and commitments, and transforming organizational assets and structures (Teece, Pisano, & Shuen, 1997; Teece, 2007). These processes have historically been rooted in managerial cognition, entrepreneurial judgment, and organizational learning (Helfat & Peteraf, 2015; Argote & Miron-Spektor, 2011).

However, advances in artificial intelligence (AI)—particularly machine learning and autonomous systems—have begun to reshape the mechanisms underlying sensing, seizing, and transforming. AI systems are increasingly capable of continuous environmental scanning, predictive modeling, optimization, and iterative experimentation (Brynjolfsson, Rock, & Syverson, 2017). In R&D and innovation contexts, machine learning reduces the cost of experimentation and expands the search space for novel solutions (Cockburn, Henderson, & Stern, 2018). These capabilities suggest that AI systems may operationalize core components of dynamic capabilities.

Building on this foundation, we conceptualize agentic AI systems as socio-technical actors embedded within organizational processes, capable of contributing to strategic renewal through distributed agency. Rather than replacing managerial decision-making, these systems participate in and reshape the processes of opportunity recognition, experimentation, and capability reconfiguration.

3.2. Distributed Agency in Innovation

Traditional theories implicitly assume that innovation agency resides in human actors—managers, entrepreneurs, and teams. Yet digital innovation research demonstrates that generativity and recombination increasingly occur across distributed networks of actors and technologies (Yoo, Henfridsson, & Lyytinen, 2010; Nambisan, Wright, & Feldman, 2019). AI systems extend this logic by performing adaptive and learning-based functions that influence strategic trajectories.

Leonardi (2011) argues that material artifacts shape organizational action through affordances. AI systems differ from traditional artifacts because their affordances evolve through learning. As models update based on data feedback, they generate new strategic options and constrain others. Thus, agency becomes distributed across human and algorithmic actors operating within shared decision architectures.

We define **distributed innovation agency** as a configuration in which initiative, variation generation, and adaptation are co-produced by human and AI actors within governance boundaries established by the firm. In this view, agentic systems contribute to strategic renewal through three interconnected mechanisms: (1) continuous opportunity discovery, (2) autonomous variation and selection, and (3) rapid capability reconfiguration.

3.3. Mechanism 1: Continuous Opportunity Discovery (Algorithmic Sensing)

The sensing dimension of dynamic capabilities involves identifying emerging opportunities and threats (Teece, 2007). Traditionally, sensing relies on managerial scanning, interpretation, and intuition. However, AI systems enable continuous, real-time environmental monitoring across vast datasets, detecting patterns beyond human cognitive limits.

Machine learning models can identify market shifts, consumer preferences, and technological signals through large-scale data analysis (Brynjolfsson et al., 2017). In innovation contexts, AI-driven analytics enhance opportunity recognition by predicting unmet needs or technological complementarities (Cockburn et al., 2018).

In our framework, agentic systems perform algorithmic sensing by:

- Continuously scanning structured and unstructured data sources.

- Generating predictive signals regarding emerging opportunities.
- Alerting or autonomously triggering exploratory initiatives.

This shifts sensing from episodic managerial activity to ongoing computational process, expanding the scope and speed of opportunity discovery.

3.4. Mechanism 2: Autonomous Variation and Selection (Algorithmic Seizing)

Seizing involves mobilizing resources and making strategic commitments (Teece, 2007). In innovation processes, this often entails experimentation, prototyping, and investment decisions. AI systems increasingly automate experimentation through simulation, A/B testing, and optimization algorithms.

Cockburn et al. (2018) argue that machine learning reduces the cost of searching complex solution spaces, enabling rapid exploration of design alternatives. This capacity aligns with evolutionary theories of innovation emphasizing variation and selection (Nelson & Winter, 1982). AI systems generate numerous variants, evaluate outcomes through feedback loops, and select high-performing options.

In digital platform environments, algorithmic coordination structures innovation pathways and allocates visibility or resources (Tiwana, Konsynski, & Bush, 2010). Agentic systems may autonomously allocate marketing budgets, adjust pricing strategies, or refine product features based on real-time data.

Within our framework, autonomous variation and selection function as algorithmic seizing processes that:

- Generate and test strategic alternatives.
- Allocate resources based on predictive optimization.
- Iteratively refine products or processes without continuous human intervention.

Human actors retain oversight authority, but initiative increasingly originates within AI-driven experimentation loops.

3.5. Mechanism 3: Rapid Capability Reconfiguration (Algorithmic Transforming)

The transforming dimension of dynamic capabilities refers to reconfiguring assets and structures to sustain competitiveness (Teece, 2007). Organizational learning theory suggests that transformation emerges from cumulative experience and knowledge integration (Argote & Miron-Spektor, 2011).

AI systems accelerate transformation by enabling real-time process reconfiguration. For example, predictive maintenance systems dynamically adjust operations, while adaptive supply chain algorithms reallocate logistics resources. These changes occur continuously rather than episodically.

Raisch and Krakowski (2021) highlight that AI reshapes managerial roles, shifting from direct decision-making to oversight and orchestration. As AI systems reconfigure workflows autonomously, managers focus on governance design, objective setting, and ethical supervision.

In this framework, algorithmic transforming involves:

- Automated process adjustments based on predictive feedback.
- Dynamic reallocation of organizational resources.
- Continuous updating of routines and operating models.

Transformation becomes embedded in algorithmic cycles rather than discrete strategic initiatives.

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3.6. Governance and Boundary Conditions
While agentic systems expand innovation capacity, they introduce governance challenges. Algorithmic opacity may reduce transparency and accountability (Pasquale, 2015). Fairness and ethical considerations require explicit oversight mechanisms (Binns, 2018).

Thus, distributed innovation agency operates within bounded governance structures characterized by:

- Clearly defined objective functions and constraints.
- Human override and monitoring capabilities.
- Ethical and compliance safeguards.

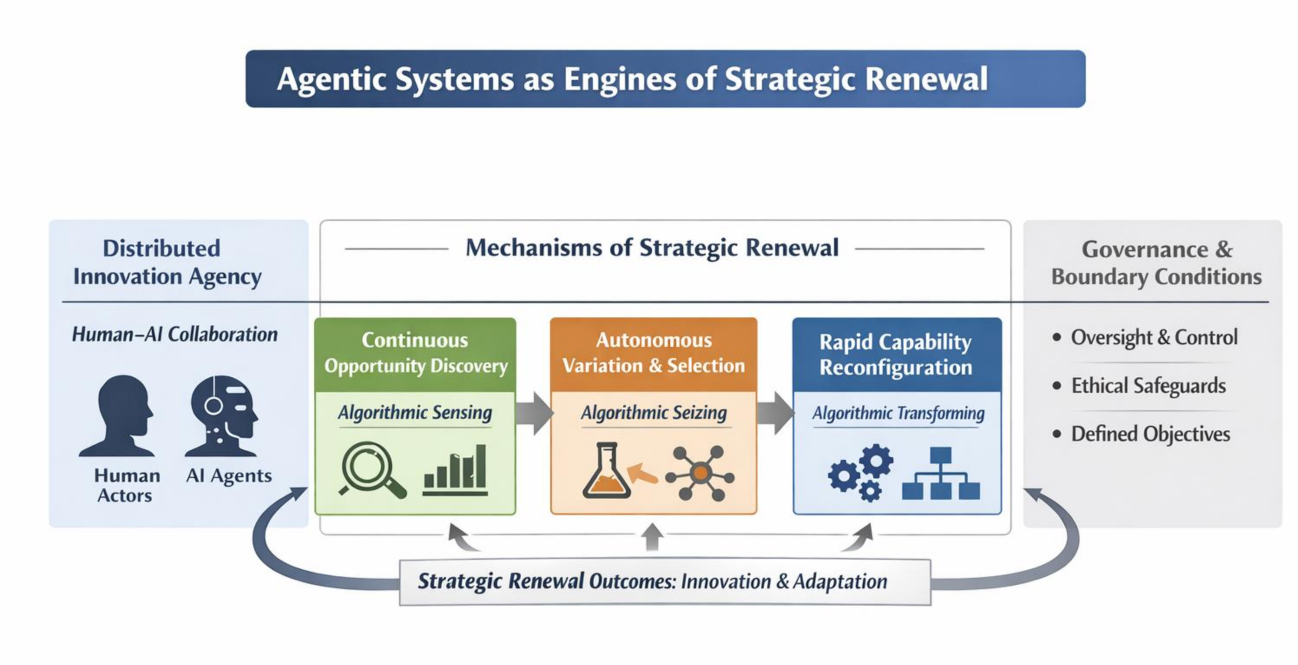
Strategic renewal under agentic systems depends not only on technological capability but also on institutional design.

3.7. Propositions for Future Research
Based on this framework, we propose:

Proposition 1: The greater the degree of agentic AI integration in sensing processes, the broader and faster the firm's opportunity discovery capacity.

Proposition 2: Autonomous variation and selection mechanisms increase innovation velocity but require complementary human governance to ensure strategic alignment.

Proposition 3: Firms that integrate AI-driven transforming processes with strong managerial cognitive capabilities achieve more sustained strategic renewal.



4. Explanation of the Conceptual Model: Agentic Systems as Engines of Strategic Renewal
The model conceptualizes **agentic AI systems** as embedded actors within the dynamic capabilities architecture of the firm. It explains how strategic renewal emerges through *distributed innovation agency* across human and AI actors, structured around three core mechanisms aligned with sensing, seizing, and transforming (Teece, Pisano, & Shuen, 1997; Teece, 2007).

4.1. Foundational Layer: Distributed Innovation Agency
At the left side of the model, innovation originates from **human–AI collaboration**, conceptualized as distributed agency.

Theoretical grounding

Strategic renewal has traditionally been attributed to managerial cognition and entrepreneurial initiative (Agarwal & Helfat, 2009). Dynamic capabilities literature emphasizes that managers interpret signals, allocate resources, and reconfigure assets (Helfat & Peteraf, 2015).

However, digital innovation research shows that innovation increasingly emerges from socio-technical networks rather than isolated individuals (Yoo, Henfridsson, & Lyytinen, 2010; Nambisan, Wright, & Feldman, 2019). AI systems contribute actively to this network through adaptive learning and predictive modeling.

Leonardi (2011) argues that technologies shape action through affordances. AI differs from traditional technologies because its affordances evolve via learning. As such, agency becomes partially embedded in algorithmic systems.

Model Implication

Distributed innovation agency means:

- Humans define goals, constraints, and governance structures.
- AI agents execute sensing, experimentation, and adaptation processes.
- Innovation emerges from the interaction between both.

This reflects a shift from **human-centered innovation** to **hybrid socio-technical innovation systems**.

4.2. Mechanism 1: Continuous Opportunity Discovery (Algorithmic Sensing)

This mechanism corresponds to the *sensing* dimension of dynamic capabilities.

Theoretical Grounding

Sensing involves identifying emerging opportunities and threats (Teece, 2007). Traditionally, managers scan environments using experience and intuition.

AI expands this function dramatically. Machine learning systems process large-scale datasets to detect weak signals, patterns, and predictive trends (Brynjolfsson, Rock, & Syverson, 2017).

In innovation contexts, AI reduces search costs and enhances discovery by identifying non-obvious technological combinations (Cockburn, Henderson, & Stern, 2018).

How the model operationalizes sensing

Agentic systems perform:

- Real-time market analytics
- Pattern recognition across unstructured data
- Predictive opportunity modeling
- Automated alerts and exploratory triggers

This transforms sensing from episodic managerial activity to **continuous computational monitoring**.

Strategic implication

Firms integrating algorithmic sensing:

- Broaden opportunity search space
- Increase speed of detection
- Reduce cognitive biases in environmental scanning

However, overreliance may narrow strategic imagination if objective functions are poorly specified.

4.3. Mechanism 2: Autonomous Variation and Selection (Algorithmic Seizing)

This corresponds to the *seizing* phase of dynamic capabilities.

Theoretical Grounding
Seizing involves mobilizing resources and committing to strategic initiatives (Teece, 2007). Evolutionary theory conceptualizes innovation as variation–selection processes (Nelson & Winter, 1982).
AI operationalizes this evolutionary logic by:
- Generating multiple design alternatives
- Running simulations and A/B experiments
- Selecting high-performing variants

Cockburn et al. (2018) argue that AI lowers experimentation costs and expands solution spaces.
In platform ecosystems, algorithmic coordination governs resource allocation and innovation pathways (Tiwana, Konsynski, & Bush, 2010).
Model Interpretation
Autonomous variation and selection include:
- Algorithmic product testing
- Dynamic pricing optimization
- Automated resource reallocation
- AI-driven portfolio optimization

Human managers oversee high-level strategy but increasingly rely on AI-driven experimentation loops.
Strategic implication
This increases:
- Innovation velocity
- Experimentation scale
- Precision in resource allocation

But it introduces governance challenges concerning alignment and accountability.
4.4. Mechanism 3: Rapid Capability Reconfiguration (Algorithmic Transforming)
This mechanism aligns with the *transforming* dimension.
Theoretical grounding
Transforming involves recombining and reconfiguring assets to maintain competitiveness (Teece, 2007). Organizational learning emphasizes cumulative adaptation (Argote & Miron-Spektor, 2011).
AI accelerates transformation through real-time process adjustment:
- Predictive maintenance
- Adaptive supply chain routing
- Autonomous workflow redesign

Raisch and Krakowski (2021) describe how AI reshapes managerial roles, shifting them toward orchestration rather than direct execution.
Model Interpretation
Algorithmic transforming entails:
- Continuous process optimization
- Automated reallocation of organizational resources
- Adaptive restructuring of routines

Transformation becomes ongoing rather than episodic.
Strategic Implication
Firms develop:
- Higher adaptive speed
- Continuous strategic renewal

- Greater operational resilience

Yet sustained advantage requires complementary managerial cognitive capabilities (Helfat & Peteraf, 2015).

4.5. Governance and Boundary Conditions

The right side of the model emphasizes oversight and constraints.

Theoretical grounding

Algorithmic systems raise transparency and accountability concerns (Pasquale, 2015).

Fairness and responsibility in AI require governance structures and ethical safeguards (Binns, 2018).

Raisch and Krakowski (2021) argue that the automation–augmentation paradox necessitates hybrid control systems.

Governance dimensions in the model

- Clearly defined objective functions
- Human override authority
- Ethical and regulatory safeguards
- Monitoring and auditability mechanisms

Without governance, distributed agency may produce strategic drift or ethical failures.

4.6. Strategic Renewal Outcomes

At the bottom of the model, the feedback loop leads to:

Innovation & Adaptation

Strategic renewal emerges when:

- Algorithmic sensing identifies opportunities
- AI-driven experimentation selects viable innovations
- Processes are reconfigured dynamically
- Human oversight ensures alignment

The system operates as a **continuous adaptive cycle**, reinforcing competitive advantage through sustained renewal.

Integrated Theoretical Contribution

This model extends existing literature by:

1. Expanding dynamic capabilities to include algorithmic actors.
2. Reconceptualizing innovation as distributed socio-technical agency.
3. Integrating AI governance into strategic renewal theory.

It reframes AI not merely as a productivity tool but as a structural component of strategic agency.

5. Discussion

This article set out to address a central question: **who innovates when AI acts?** The conceptual model developed here positions agentic AI systems not as passive tools, but as embedded participants in the dynamic capabilities architecture of the firm. The discussion elaborates on how this reconceptualization reshapes our understanding of innovation, strategic agency, and organizational adaptation.

5.1. Reframing Innovation as Hybrid Agency

The dominant view in strategic management treats innovation as the outcome of human cognition, entrepreneurial initiative, and managerial orchestration (Agarwal & Helfat, 2009; Helfat & Peteraf, 2015). Even within dynamic capabilities theory, sensing, seizing, and transforming are implicitly grounded in managerial intentionality (Teece, 2007).

However, as AI systems increasingly perform predictive analytics, optimization, experimentation, and autonomous adjustment, innovation becomes partially enacted by algorithmic systems. Brynjolfsson, Rock, and Syverson (2017) argue that AI functions as a general-purpose technology, reshaping production and knowledge processes. Cockburn, Henderson, and Stern (2018) further show that AI expands the solution search space in innovation, fundamentally altering the structure of discovery.

In this context, innovation cannot be attributed solely to human actors. Instead, it emerges from **hybrid socio-technical configurations** in which human judgment and algorithmic computation interact continuously. This reframing aligns with digital innovation research, which emphasizes generativity and distributed processes across technical and social actors (Yoo, Henfridsson, & Lyytinen, 2010; Nambisan, Wright, & Feldman, 2019). Agentic systems intensify this distributed logic by introducing adaptive, learning-based decision-making capacities.

5.2. Reinterpreting Dynamic Capabilities Under Algorithmic Conditions

The model suggests that AI systems increasingly operationalize core elements of dynamic capabilities.

- **Sensing** becomes continuous and data-driven through algorithmic pattern recognition.
- **Seizing** is partially automated via large-scale experimentation and optimization loops.
- **Transforming** becomes ongoing through real-time process reconfiguration (Teece, 2007).

This evolution does not eliminate managerial roles but alters their locus. Helfat and Peteraf (2015) emphasize managerial cognitive capabilities as microfoundations of dynamic capabilities. Yet when AI systems generate strategic options and evaluate alternatives, the cognitive boundary of the firm expands to include algorithmic reasoning. Managers transition from primary decision-makers to designers and overseers of socio-technical systems.

Raisch and Krakowski (2021) describe this shift as the automation–augmentation paradox: AI simultaneously substitutes and complements human decision-making. In strategic renewal contexts, AI augments opportunity identification while automating experimentation, thereby accelerating adaptation cycles.

5.3. Acceleration and Scale of Innovation Processes

One key feature of agentic systems is their capacity to accelerate innovation velocity. Evolutionary theories of innovation emphasize variation, selection, and retention (Nelson & Winter, 1982). Traditionally, these processes are constrained by cognitive limits, organizational inertia, and experimentation costs.

AI significantly reduces these constraints. Cockburn et al. (2018) demonstrate that machine learning reduces the cost of searching complex technological landscapes. Algorithmic experimentation allows firms to test thousands of alternatives simultaneously, dramatically increasing variation generation and selection precision.

This acceleration has structural consequences. Strategic renewal, once episodic and reactive, becomes continuous and embedded in operational systems. Digital platforms illustrate this phenomenon, where algorithmic coordination governs experimentation and adaptation at ecosystem scale (Tiwana, Konsynski, & Bush, 2010).

5.4. Governance Tensions and Strategic Risk

While agentic systems enhance adaptive capacity, they also introduce structural risks. Pasquale (2015) highlights the opacity of algorithmic decision-making, raising concerns about transparency and accountability. As AI systems autonomously adjust pricing, resource allocation, or product features, understanding causal mechanisms becomes more difficult.

Binns (2018) argues that fairness and accountability in machine learning require explicit governance mechanisms. Without oversight, distributed agency may generate unintended biases or strategic drift.

Thus, strategic renewal under AI conditions is not purely a capability question but also a governance challenge. The effectiveness of agentic systems depends on clearly specified objective functions, monitoring structures, and alignment mechanisms. Absent such structures, automation may amplify errors at scale.

5.5. Boundary Conditions of Agentic Strategic Renewal

The model also implies important boundary conditions. First, AI-driven renewal depends on data quality and infrastructure maturity (Brynjolfsson et al., 2017). Without complementary investments in digital architecture, algorithmic sensing and transforming remain constrained.

Second, human interpretive capacity remains critical. Even advanced AI systems operate within objective functions defined by humans. Mis-specified goals can lead to optimization of local metrics at the expense of long-term strategy. Helfat and Peteraf (2015) suggest that managerial cognitive capabilities remain essential for interpreting algorithmic outputs and reframing strategic direction.

Third, industry context matters. In highly digital and data-rich environments, AI-driven renewal may dominate. In knowledge-intensive or tacit domains, human judgment may remain primary. Digital innovation research suggests that the degree of reprogrammability and modularity influences the extent of algorithmic participation in innovation (Yoo et al., 2010).

5.6. Strategic Renewal as Continuous Adaptive Loop

The discussion underscores that agentic systems embed strategic renewal into operational cycles. Instead of discrete strategic planning phases, renewal becomes an ongoing adaptive loop:

1. Algorithmic sensing identifies signals.
2. Autonomous experimentation evaluates alternatives.
3. Real-time reconfiguration updates capabilities.
4. Feedback refines objectives and models.

This recursive cycle resembles evolutionary adaptation but at unprecedented computational speed. As Nelson and Winter (1982) argue, routines shape firm behavior; under AI conditions, routines themselves become dynamically adjustable through algorithmic feedback loops.

Consequently, competitive advantage may increasingly depend on the firm's ability to design and govern these adaptive socio-technical systems rather than solely on superior human insight.

5.7. Redefining the Innovator

Ultimately, the discussion returns to the central question: who innovates when AI acts?

The evidence suggests that innovation under agentic systems is neither purely human nor purely machine-driven. It is **collectively produced** within structured socio-technical systems. Humans define purpose, boundaries, and values. AI systems generate variation, analyze data, and execute adaptation at scale.

Strategic renewal thus becomes a property of the **system architecture** rather than of individual actors alone. Firms that effectively integrate algorithmic sensing, autonomous experimentation, and adaptive reconfiguration within governance constraints may achieve sustained renewal.

6. Theoretical Implications

The proposed model of agentic systems as engines of strategic renewal generates several important theoretical implications for strategic management, innovation theory, organizational learning, and digital transformation research.

6.1. Extending Dynamic Capabilities to Include Algorithmic Agency

Dynamic capabilities theory conceptualizes sensing, seizing, and transforming as organizational capacities grounded in managerial cognition and intentionality (Teece, Pisano, & Shuen, 1997; Teece, 2007). Microfoundations research further emphasizes managerial cognitive capabilities as central drivers of adaptation (Helfat & Peteraf, 2015).

The model developed in this article extends this theoretical architecture by introducing **algorithmic actors as partial carriers of dynamic capabilities**. Agentic AI systems perform sensing through predictive analytics, seizing through autonomous experimentation, and transforming through real-time process reconfiguration.

This implies that dynamic capabilities are no longer exclusively human-embedded but may be partially instantiated in computational systems. The unit of analysis shifts from managerial cognition alone to **socio-technical capability systems**, expanding the microfoundations of strategy.

6.2. Reconceptualizing Innovation as Distributed Agency

Traditional theories of innovation emphasize entrepreneurial initiative, top management agency, and organizational routines (Agarwal & Helfat, 2009; Nelson & Winter, 1982). Even digital innovation research, while acknowledging distributed actors, often assumes human intentionality as primary (Yoo, Henfridsson, & Lyytinen, 2010).

The present framework advances theory by conceptualizing **distributed innovation agency**, where innovation outcomes emerge from interaction between human and AI actors. This challenges the implicit anthropocentric bias in strategy and innovation research.

Innovation becomes a property of the socio-technical configuration rather than a purely human act. This aligns with the view that digital technologies reshape organizing logics (Nambisan, Wright, & Feldman, 2019), but moves further by treating AI as an adaptive, learning-based participant in innovation processes.

6.3. Reframing the Microfoundations of Strategic Renewal

Microfoundations research examines how individual-level actions aggregate into organizational outcomes (Helfat & Peteraf, 2015). The rise of agentic systems complicates this aggregation logic. When AI systems autonomously generate and evaluate alternatives, innovation emerges from hybrid cognition.

This suggests that the microfoundations of strategic renewal must incorporate:

- Algorithmic decision rules
- Objective function design
- Human–AI interaction architectures

Rather than focusing solely on managerial traits or routines, future theory must account for how **algorithmic architectures shape strategic behavior**.

6.4. Integrating Evolutionary Theory with Computational Adaptation

Evolutionary economics conceptualizes innovation as variation, selection, and retention (Nelson & Winter, 1982). Agentic AI systems operationalize this evolutionary logic computationally by generating high-volume variation and performing rapid selection through predictive optimization (Cockburn, Henderson, & Stern, 2018).

This suggests a theoretical convergence between evolutionary theory and computational adaptation. Under AI conditions, evolutionary processes become accelerated and partially automated. Selection mechanisms shift from market feedback alone to algorithmic simulation and real-time experimentation.

Thus, strategic renewal can be reconceptualized as a **computationally intensified evolutionary cycle**.

6.5. Reinterpreting the Automation–Augmentation Paradox

The automation–augmentation paradox suggests that AI both substitutes for and complements human decision-making (Raisch & Krakowski, 2021). The present model extends this paradox to the domain of innovation and renewal.

Agentic systems automate experimentation and adaptation while augmenting opportunity recognition and decision breadth. The theoretical implication is that innovation agency becomes layered rather than replaced. Human roles shift toward orchestration, governance, and purpose definition.

This reframes debates about technological substitution by emphasizing **structural reconfiguration of agency** rather than displacement.

6.6. Embedding Governance into Strategic Theory

Governance has often been treated separately from capability theory. However, algorithmic opacity and accountability challenges (Pasquale, 2015; Binns, 2018) indicate that governance structures directly shape how distributed agency operates.

The model implies that governance mechanisms are not peripheral controls but **integral boundary conditions of dynamic capabilities under AI conditions**. Objective specification, ethical safeguards, and oversight architectures become foundational components of strategic renewal.

This integrates AI governance into the core of strategic management theory rather than treating it as an external regulatory issue.

6.7. Redefining the Locus of Competitive Advantage

Brynjolfsson, Rock, and Syverson (2017) argue that AI's productivity gains depend on complementary investments. The framework suggests that competitive advantage increasingly depends on the firm's ability to design, integrate, and govern agentic systems within renewal processes.

Thus, the locus of advantage shifts from isolated human insight to **system-level design of adaptive socio-technical architectures**. Theoretically, this reframes resource-based and capability-based views toward digital system integration as a strategic asset.

7. Practical Implications

The proposed model of agentic systems as engines of strategic renewal carries important implications for how organizations design structures, allocate authority, build capabilities, and govern AI-enabled innovation processes. These implications follow directly from research on dynamic capabilities, AI integration, and digital transformation.

7.1. Redesigning Organizational Roles Around Human–AI Collaboration

As AI systems increasingly perform sensing, experimentation, and adaptation, managerial roles shift from direct decision-making toward orchestration and system design. Research shows that AI adoption reshapes work by both automating and augmenting tasks (Raisch & Krakowski, 2021).

Practically, firms should:

- Redefine managerial responsibilities toward goal-setting, supervision, and exception handling.
- Develop hybrid teams where domain experts collaborate with data scientists and AI engineers.
- Train leaders to interpret algorithmic outputs rather than rely solely on intuition.

Managers remain essential, but their value lies increasingly in defining objectives, resolving ambiguity, and aligning AI outputs with strategic intent (Helfat & Peteraf, 2015).

7.2. Building Continuous Sensing Capabilities

Dynamic capabilities research emphasizes sensing as a prerequisite for renewal (Teece, 2007). AI systems dramatically expand environmental scanning capacity (Brynjolfsson, Rock, & Syverson, 2017).

Organizations should:

- Invest in integrated data infrastructures across functions.
- Implement real-time analytics dashboards.
- Use AI-driven predictive tools for market, customer, and competitor analysis.

However, data quality and interoperability are critical boundary conditions. Without reliable data pipelines, algorithmic sensing cannot function effectively.

7.3. Institutionalizing Experimentation at Scale

AI reduces the cost and time of experimentation (Cockburn, Henderson, & Stern, 2018). Firms can operationalize this advantage by embedding autonomous testing mechanisms into product development, pricing strategies, and service design.

Practical actions include:

- Deploying automated A/B testing platforms.
- Allowing AI systems to run micro-experiments within predefined risk thresholds.
- Integrating experimentation metrics directly into decision dashboards.

This shifts innovation from episodic projects to continuous adaptive cycles, consistent with evolutionary innovation processes (Nelson & Winter, 1982).

7.4. Designing Governance and Oversight Structures

Algorithmic opacity introduces risks related to bias, accountability, and misalignment (Pasquale, 2015; Binns, 2018). Therefore, governance must be embedded into AI-driven renewal systems.

Organizations should:

- Define clear objective functions aligned with long-term strategy.
- Establish AI oversight committees or governance boards.
- Implement audit trails and explainability protocols.
- Maintain human override mechanisms for high-stakes decisions.

Raisch and Krakowski (2021) emphasize that balancing automation and augmentation requires deliberate structural design. Governance is not an add-on but a core component of AI-enabled renewal.

7.5. Aligning Incentives with Adaptive Learning

Strategic renewal requires continuous adaptation (Agarwal & Helfat, 2009). AI systems amplify adaptation speed, but incentive systems must support experimentation rather than punish short-term variance.

Firms should:

- Reward data-driven experimentation.
- Encourage cross-functional collaboration around AI initiatives.
- Incorporate adaptive performance metrics rather than static KPIs.

This ensures that organizational culture complements algorithmic agility.

7.6. Investing in Complementary Assets

AI's performance impact depends heavily on complementary investments (Brynjolfsson et al., 2017). Technology alone does not generate advantage.

Organizations must invest in:

- Data infrastructure and cloud capabilities.
- Talent development in AI literacy.

- Cross-functional integration between IT and business units.

Strategic renewal emerges from socio-technical integration rather than standalone AI tools (Nambisan, Wright, & Feldman, 2019).

7.7. Managing Strategic Risk in Autonomous Systems

Agentic systems can scale errors rapidly. Poorly specified goals may lead to unintended optimization outcomes. Therefore, firms must implement risk management mechanisms such as:

- Scenario simulations before full deployment.
- Gradual autonomy escalation (human-in-the-loop → human-on-the-loop → supervised autonomy).
- Continuous monitoring of unintended consequences.

These safeguards reduce the risk of strategic drift and reputational damage.

7.8. Competing on Adaptive Speed

Under AI conditions, competitive advantage increasingly depends on the ability to adapt faster than rivals. AI-driven sensing, experimentation, and reconfiguration shorten feedback loops (Teece, 2007).

Firms that effectively integrate these mechanisms may achieve:

- Faster product iteration cycles
- More precise resource allocation
- Greater resilience to environmental shocks

Thus, the practical challenge shifts from executing static strategies to designing adaptive socio-technical systems capable of ongoing renewal.

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