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Exploring the Reconstruction of the Micro foundations of Dynamic Capabilities in the Age of Artificial Intelligence

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Abstract

By analyzing how AI alters the sensing, seizing, and reconfiguring processes, this study rethinks the micro-foundations of dynamic capabilities (DC) in the era of artificial intelligence. The emergence of AI introduces new actors, mechanisms, and decision logics that drastically change how businesses perceive their surroundings and react to change. Traditional Dynamic Capabilities theory is based on human cognition, routines, and experiential judgment. This study creates a hybrid framework with hybrid actors, algorithmic mechanisms, and hybrid decision logic based on dynamic capability theory, organizational information processing, human–AI collaboration, and algorithmic agency research. The analysis demonstrates that AI is an emerging meta-capability that increases the scope and speed of environmental sensing, rather than just a technical tool, accelerates resource reconfiguration through automation and digital replication and improves strategic seizing through simulation, prediction, and optimization. These changes result in a hybrid human-AI configuration rather than a human-centric model for capability formation. Empirical research is necessary as a conceptual study to verify the suggested claims and investigate cross-industry variations and the dynamics of human–AI interaction. Practically, firms must redesign their sensing, decision-making, and reconfiguration systems to integrate AI, while managers need new competencies in orchestrating human–AI collaboration and overseeing algorithmic governance. This study provides one of the earliest systematic frameworks for understanding how AI reshapes the

micro foundations of dynamic capabilities and offers a new theoretical lens for explaining enterprise evolution in the AI era.

Keywords: Artificial Intelligence (AI), Dynamic Capabilities (DC), Human–AI Collaboration

Introduction

With breakthroughs and rapid development in AI technology, AI has permeated all aspects of production and life. Enterprises, as the core entities of the socio-economic system, are also being transformed by AI . AI is changing how enterprises organize learning, make management decisions, and allocate resources. To adapt to changes in the external environment, enterprises need to continuously update and adapt their capability systems.

Dynamic capability theory effectively explains this core capability of enterprises in responding to changes in the external environment. This capability describes the process of enterprises adapting to external changes from three dimensions: sensing (identifying opportunities and threats), seizing (formulating and configuring strategic actions), and reconfiguring (reorganizing the resource base) (Teece, 2007). These three dimensions not only explain the spatiotemporal sequence of enterprises adapting to the external environment but also logically progress, concisely summarizing different levels of dynamic capability from simple to complex. The core of dynamic capability theory is its micro-foundation, and the existing dynamic capability framework assumes that its micro-foundation is established in three aspects. First, dynamic capabilities are primarily implemented by people, who are both the source and carrier of these capabilities. Second, the process of putting dynamic capabilities into practice entails recognizing shifts in the outside world to make strategic decisions more understandable; this is basically a cognitive process. People adjust organizational behavior and reallocate organizational resources by using knowledge, experience, organizational conventions, and iterative learning to develop an accurate understanding of environmental changes as well as their own resources and capabilities.Third, heuristic exploration, managerial intuition, experience-driven methods, and bounded rationality form the foundation of the decision-making logic associated with the application of dynamic capabilities.

However, these three presumptions have been called into question by AI's use in business and enterprise management, which has changed the micro-foundations of dynamic capabilities. A growing body of recent research indicates that AI introduces new forms of cognition, agency, and collaboration that radically alter organizational capabilities. According to Faraj et al. (2018), algorithmic systems now have algorithmic agency, which allows them to act, suggest, categorize, and make decisions that affect organizational procedures without continual human oversight. This casts doubt on the conventional wisdom that only human actors possess agency. Building on this change, Raisch and Krakowski (2021) present the idea of managerial augmentation, arguing that AI improves human judgment by increasing analytical capacity, lowering cognitive biases, and improving decision quality rather than merely automating managerial tasks. In parallel, Shrestha et al. (2019) advance the notion of hybrid intelligence, showing that optimal organizational decision-making emerges when human contextual reasoning is combined with AI's computational strengths, creating superior joint performance compared to either human or machine alone. Complementing these perspectives, von Krogh (2018) demonstrates that AI extends significantly firms' sensing capabilities by enabling the detection of weak signals, anomaly patterns, and emerging trends that humans often overlook. Collectively, these studies reveal that AI transforms not only organizational tasks but also the underlying micro-foundations —agency, cognition, and sensing—through which dynamic capabilities are built.

In summary, existing theoretical frameworks for dynamic capabilities cannot accommodate algorithmic logic, and the three fundamental elements of dynamic capabilities (actor, mechanism and logic) have all changed. While the above research touches upon some aspects, it has gaps in three key areas: first, the executing agent is missing; second, the execution mechanism is missing; and third, the decision-making logic is missing. A comprehensive and systematic framework is lacking to explain how AI alters the micro-foundations of dynamic capabilities.

Therefore, this paper attempts to propose an " AI-driven micro-foundation framework for dynamic capabilities" to explain the impact and mechanism of AI on dynamic capability frameworks. The contributions of this paper are threefold: first, it redefines the micro-foundation of dynamic capabilities, it is the main contribution; second, it proposes a human-machine hybrid dynamic capability framework; and third, the related propositions provide a reference for future empirical research on AI-driven dynamic capabilities. Rather than extending existing dynamic capabilities theory, this paper reconstructs its micro-foundations by theorizing algorithmic agency and human–AI hybrid logic as constitutive elements of capability formation.

Literature Review

Dynamic Capabilities and Their Micro-Foundations

Dynamic capabilities theory（Teece，2007) has become one of the core theories explaining how companies continuously adapt and grow in complex and ever-changing environments, thereby maintaining and enhancing their core competitiveness. It mainly includes three basic dimensions: sensing (identifying opportunities and threats), seizing (formulating and configuring strategic actions), and reconfiguring (restructuring resource base) (Teece, 2007) . These three dimensions describe the key action combinations that enable companies to adjust their internal strategic resource capabilities in response to changes in the external environment, becoming a key mechanism for corporate adaptation and evolution, allowing companies to continuously rebuild their resources, processes, and strategic boundaries (Helfat & Winter, 2011) .

The "micro-foundations" perspective of dynamic capabilities theory has become key to explaining its underlying logic. This perspective emphasizes that dynamic capabilities originate from deeper individual actions, managerial cognition, organizational routines, and learning mechanisms, rather than abstract macro-level capability descriptions (Felin et al., 2012). Helfat & Peteraf (2015) further proposed the "managerial cognitive micro-foundations " framework, pointing out that managers' attention allocation, judgment logic, experience accumulation, and explanatory structures constitute the foundation for sensing, seizing, and reconfiguring. This view lays the foundation for the "human-centric assumption" of dynamic capabilities theory, namely that the adaptability of enterprises mainly stems from human perception, judgment, and decision-making abilities (Augier & Teece, 2009). However, this human-centric assumption has also brought significant controversy to dynamic capabilities theory.

Felin & Foss (2005) pointed out that without a micro-foundation, dynamic capabilities easily become descriptive "black boxes". Therefore, clarifying "who executes the capability" and "how the capability is formed" has become an important research task in this field. Existing literature generally agrees that the essence of dynamic capabilities is an adaptive system composed of human cognition, organizational routines, collaborative relationships, and learning processes (Hodgkinson & Healey, 2011;Helfat & Peteraf , 2015). However, this system is facing unprecedented challenges in the face of the rise of artificial intelligence. The rise of AI and its penetration into daily management and operations have led to AI, such as various intelligent agents, gradually becoming one of the main actors in capability execution, and in some scenarios, performing tasks jointly with humans. The formation of corporate capabilities is also becoming increasingly closely related to AI; For example, the core capabilities of many AI- native companies are largely derived from AI. This has shaken the original micro-foundation of dynamic capabilities, requiring new fundamental structures and theoretical explanations.

AI in Organizations: Agency, Cognition, and Coordination

The rise of artificial intelligence (AI) is fundamentally changing how organizations operate, including information processing, decision-making logic, knowledge structures, and action patterns (McAfee & Brynjolfsson, 2017; Jarrahi, 2018). Unlike traditional software and information systems, modern AI possesses the capabilities of autonomous learning, predictive reasoning, iterative optimization, and generative inference, enabling it to undertake cognitive and coordinating tasks previously performed by humans (Faraj et al., 2018). Therefore, understanding how AI acts as a "quasi-agent" within organizations, altering cognitive agents, expanding cognitive boundaries, and redefining collaborative structures to enhance or replace human work is a core task in explaining the future evolution of organizational capabilities.

First, AI has introduced new "algorithmic agencies". Faraj, Pachidi & Sayegh (2018) point out that as AI systems acquire the ability to autonomously recognize patterns, make judgments, and execute operations, algorithmic actors with agency have emerged in organizations. These algorithms not only passively execute instructions but also actively participate in decision-making processes, resource allocation, and task decomposition, thereby changing the past human-centric organizational action logic (Kellogg et al., 2020). In platform companies, fintech, and manufacturing, algorithmic agents can independently complete risk assessment, process optimization, and operational scheduling, forming a new collaborative mechanism that transcends the traditional division of labor (Newell & Marabelli , 2015).

Secondly, AI systems have profoundly changed organizational cognition. The introduction of AI has significantly enhanced an organization's information processing capability. Organizations are designed to handle uncertainty and information complexity, according to OIP theory (Galbraith, 1974). Organizational information processing can now analyze more complex datasets, simulate more complex scenarios, and update strategic choices faster thanks to AI's statistical learning and generative reasoning capabilities (Jarrahi, 2018; Song et al., 2025). According to other research, AI's generative and predictive powers increase an organization's "sensing boundary", lowering attentional constraints in information processing (OIP theory: Galbraith, 1974; Tushman & Nadler, 1978). For instance, machine learning can improve the accuracy of market scanning, risk identification, and opportunity discovery by identifying signals from vast amounts of data that are hard for humans to understand (Heine et al., 2023). Additionally, by using reinforcement learning to mimic competitor reactions and forecast the systematic impact of various strategic combinations, AI's causal inference and simulation capabilities improve businesses' capacity to seize strategic choices.More significantly, AI's knowledge structure is different from that of humans; instead of relying on accumulated experience, it relies on an ever-expanding data distribution and updated algorithmic weights, liberating organizational cognition from managers' personal experience and judgment (Rahwan et al., 2019).

Third, organizational coordination is changing due to AI. Conventional coordination depends on organizational norms, communication channels, and hierarchical structures (Grant, 1996). However, AI reduces internal friction and delays in highly digitalized environments by enabling "just-in-time coordination" through automated interfaces, predictive scheduling, and real-time data streams. AI is capable of integrating data from various departments, identifying bottlenecks, assessing options for allocating resources, and carrying out intricate procedures without the need for human coordination. In addition to increasing productivity, this "intelligent coordination layer" transforms organizational routines from being "human experience-driven" to "data and algorithm-driven". (Pentland et al., 2010).

Finally, AI triggers a dual effect of "replacement vs. enhancement." Raisch & Krakowski (2021) proposed the AI-augmentation paradox: AI can both enhance human capabilities (augmentation) and replace human tasks (automation). For example, in strategic planning scenarios, some companies use AI to provide auxiliary analysis and enhance managers' judgment; while others allow AI to independently generate decision-making suggestions or execute operational activities, thus partially replacing middle managers. Numerous studies (Ayoub et al., 2016) indicate that the optimal organizational form may be "hybrid intelligence," where humans provide situational insight, ethical judgment, and creativity, while AI provides quantitative analysis, pattern recognition, and real-time feedback, thereby building a human-machine hybrid collaborative system.

Therefore, AI can not only improve organizational efficiency, but also constitute a new "technical micro foundation " . (Menz et al., 2021), providing a new institutional foundation for organizational adaptability.

Hypothesis Development

With the accelerated penetration of artificial intelligence into enterprises, the micro-foundations of dynamic capabilities are undergoing a systemic restructuring. Traditional dynamic capability theory emphasizes that the cognition, judgment, learning, and organizational routines of human managers are the key foundations for sensing, seizing, and reconfiguring (Teece, 2007; Helfat & Peteraf , 2015) . However, with the improvement of AI's learning and iterative capabilities, the enhancement of intelligent agent capabilities, and the gradual popularization of intelligent algorithms in decision-making, the subject of dynamic capabilities is evolving from "human-centered" to "human-machine collaboration". This study proposes a shift in the micro-foundations of dynamic capabilities. To clarify the theoretical logic and hierarchy of our arguments, this study organizes the eight propositions into three analytically distinct but interrelated groups. The core propositions (P1–P3) address what fundamentally changes in the micro-foundations of dynamic capabilities in the age of artificial intelligence, emphasizing the shift from human-centered capability enactment to hybrid human–AI agency. The mechanism propositions (P4–P6) explain how these changes occur by theorizing the role of algorithmic processes—such as pattern recognition, simulation, optimization, and automation—in reshaping sensing, seizing, and reconfiguring activities. The boundary and Integrative propositions (P7–P8) specify when and under what conditions hybrid dynamic capabilities generate superior outcomes, highlighting the importance of hybrid decision logic, governance alignment, and the coordination between human judgment and algorithmic systems. Together, these propositions form a coherent framework that explains not only the reconstruction of dynamic capabilities' micro-foundations but also the conditions under which AI-enabled capability transformation becomes strategically effective. As shown in Figure 1 below:

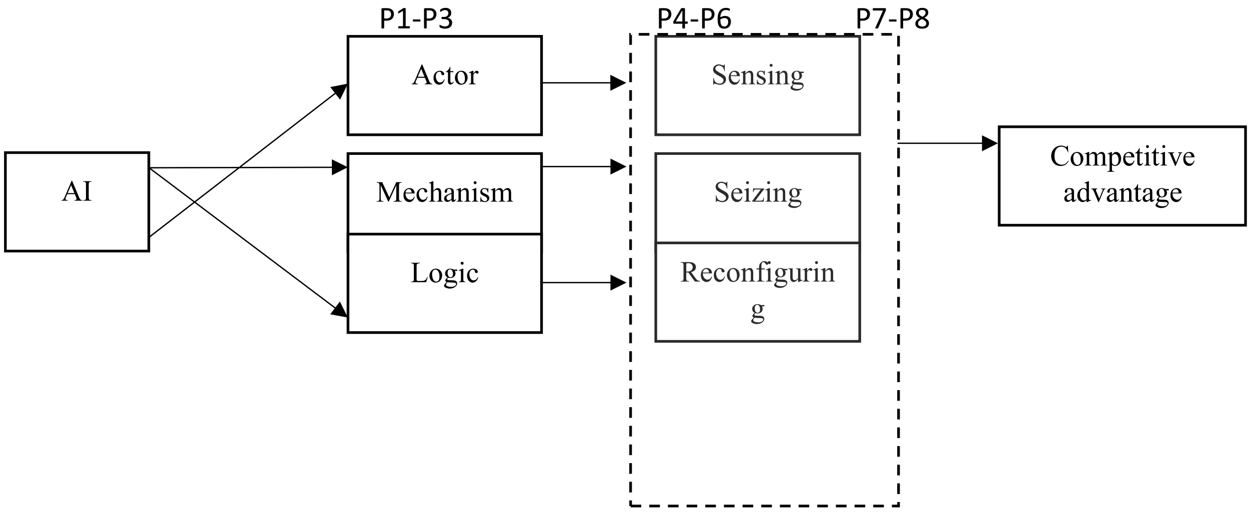

Figure 1: Conceptual framework illustrating the hierarchical structure of the proposed propositions. The model distinguishes between **core propositions (P1–P3)** that capture the fundamental transformation of dynamic capabilities' micro-foundations under artificial intelligence, **mechanism propositions (P4–P6)** that explain how algorithmic processes reshape sensing, seizing, and reconfiguring activities, and **boundary and integrative propositions (P7–P8)** that specify the contextual conditions under which AI-enabled dynamic capabilities translate into competitive advantage. Together, the framework highlights the shift from human-centered capability enactment to hybrid human–AI agency and clarifies the conditional pathways through which AI-driven capability reconfiguration becomes strategically effective. *Under which AI-enabled dynamic capabilities are more likely to form competitive advantage ultimately.*

The shift in the Micro-Foundations of Dynamic Capabilities

Due to the penetration and application of AI in enterprise management, the micro-foundations of dynamic capabilities have changed in the following three aspects:

（1） Actor: The acting agent is shifting from human managers to a human- AI hybrid agent.

（2） Mechanism: The operational mechanism shifts from human cognitive processes to intelligent algorithmic processes.

（3） Logic: Shifting from experience-driven to human-machine hybrid logic in decision-making.

The above reveals how AI, as a meta-capability, fundamentally alters the composition and operation of dynamic capabilities.

Actor: From Human Manager to Hybrid Human–AI Agents

Traditional literature on dynamic capabilities primarily focuses on managers and team members as the actors, whose core task is to drive activities such as sensing, seizing, and reconfiguring through cognitive judgment, experiential learning, and collaborative interaction (Teece, 2007). However, with the accelerated application of AI, collaboration between AI and human managers is becoming increasingly common, giving rise to a new type of actor in enterprises : the hybrid agency . Organizational activities are no longer executed solely by human managers, but rather by humans and AI jointly perceiving, making decisions, and adjusting resources.

（1） AI as one of the "acting agents", rather than merely a tool.

Faraj et al. (2018) proposed the concept of " algorithmic agency", pointing out that algorithms can influence organizational behavior—they not only provide information support but also judge, classify, recommend, and control processes. This means that AI has the characteristics of a quasi-actor: first, it can independently perform sensing tasks, such as anomaly detection and market scanning; second, it can participate in the seizing phase, such as providing strategic solutions and resource allocation suggestions; and third, it can automatically adjust processes or assign tasks during reconfiguration.

Therefore, the dynamic capabilities of the actors have shifted from a human-centered approach to a human-machine hybrid dual-core structure. Based on this, the following propositions are proposed:

P1 (Core Proposition): When artificial intelligence is embedded into organizational decision-making and operational processes, dynamic capabilities shift from being human-driven to being enacted by hybrid human–AI agents, expanding the scope and accelerating the speed of sensing, seizing, and reconfiguring.

（2） Complementarity between human and machine hybrid behavioral subjects

While AI has evolved from a tool to a key actor, the role of human managers remains crucial. AI is not a replacement for human managers, but rather an assistant. Research shows that humans and AI have significant complementary capabilities（Raisch & Krakowski, 2021）. AI excels in pattern recognition, complex computation, and unbiased data processing; humans excel in contextual understanding, fuzzy reasoning, and ethical judgment. Therefore, in the three dimensions of dynamic capabilities, AI plays a more prominent role when sensing relies on real-time data perception, or when seizing requires predictive simulation. However, when reconfiguring or when the sensing and seizing processes involve decision-making that involves ethics, values, or high ambiguity, the logic of human managers becomes more critical. Based on this, the following propositions are proposed:

P2 (Core Proposition): ：Human cognitive strengths and AI computational capabilities jointly enhance dynamic capabilities more effectively than either human or AI agency alone.

（3） The tension between human and machine hybrid actors

While human-machine hybrid entities collaborate, friction is not without its challenges, exhibiting significant governance and cognitive tensions (Raisch & Krakowski, 2021) . Because AI can substitute for human managers' tasks, managers may perceive AI not as an assistant but as a threat, impacting its adoption. Furthermore, the ambiguity, invisibility, and difficulty in explanation inherent in AI operations create a "black box" effect, potentially leading to distrust among human managers, especially in high-value, high-risk scenarios such as finance and healthcare. Finally, AI struggles to ensure accountability for decision-making outcomes, raising issues of power redistribution, attribution of responsibility, trust, and transparency (Raisch & Krakowski, 2021), creating disagreements with human managers regarding accountability and posing ethical risks. Based on this, the following propositions are proposed:

P3 (Core Proposition): ：The governance, cognitive, and accountability tensions arising from human–AI hybrid actors negatively moderate the effectiveness of dynamic capabilities, weakening the performance gains that AI could otherwise provide in sensing, seizing, and reconfiguring. This proposition highlights an inherent tension within hybrid agency, which motivates subsequent boundary propositions.

Mechanism: From Cognitive Processes to Algorithmic Processes
Traditional dynamic capability theories primarily rely on the cognitive processes of human managers, such as attention allocation, pattern recognition, analogical reasoning, and communication/collaboration (Helfat & Winter, 2011). However, the introduction of AI has introduced entirely new operating mechanisms, which not only depend on the cognition of human managers but also rely more on algorithms, models, and data to algorithmize dynamic capabilities. Specifically, this is manifested as follows:

(1) Algorithmic Sensing: Pattern recognition, anomaly detection, trend prediction
AI's mechanisms at the sensing level are primarily manifested in three algorithmic processes: First, Pattern Recognition: Machine learning extracts high-dimensional features to identify market signals, crowd behavior, or user demand patterns, finding heterogeneous information structures and opportunities faster than managers. Second, Anomaly Detection: AI can spot anomalies in vast amounts of data, such as supply chain interruptions or unusual price swings, allowing for early warnings and lowering risks and losses. Third, Trend Forecasting: AI gives businesses more insight during the sensing stage by predicting future trends using generative models and time series modeling. These algorithmic techniques increase an organization's capacity for boundary awareness, reducing the dependence of sensing on managers' scant attention and firsthand knowledge. The following claims are put forth considering this:

P4 (Mechanism Proposition): The micro-foundations of organizational sensing are greatly improved by algorithmic processes, particularly pattern recognition, anomaly detection, and trend forecasting, which allow for earlier and more precise opportunity identification.
（2）Seizing: Scenario Simulation, Decision Optimization, Risk Assessment
AI has achieved a fundamental shift in the seizing stage, moving from "judgment support" to "decision collaboration." First, scenario simulation: AI can generate various strategic scenarios and predict their outcomes, supporting strategic choices. Second, decision optimization: Through optimization algorithms, AI calculates resource allocation schemes, reducing human bias. Third, risk assessment: AI has a stronger ability to handle uncertainty, complexity, and interconnectedness, dynamically assessing risks. Therefore, the seizing mechanism has shifted from an intuitive decision-making process to a more scientific and

precise process based on evidence, prediction, and collaboration. Based on this, the following propositions are proposed:

P5 (Mechanism Proposition):AI-enabled scenario simulation, decision optimization, and risk assessment transform the micro-foundations of seizing by reducing cognitive biases and enabling more evidence-based strategic choices.

(3) Algorithmic Reconfiguring: Process Automation, Resource Scheduling, Digital Twin

During the reconfiguration phase, AI mechanisms become more concrete and executable. First, Process Automation: AI and RPA work together to enable process reengineering without human intervention, forming a self-adjusting capability. Second, Resource Allocation & Scheduling: AI dynamically matches personnel, inventory, capacity, and demand through optimized models, achieving real-time and accurate supply-demand matching and reducing opportunity loss and inventory costs . Third, Digital Twin: AI allows organizations to simulate resource structure changes in a virtual environment, providing a "risk-free experiment" for reconfiguration and reducing adjustment risks. AI makes reconfiguration faster, lower cost ,lower risk, and possesses dynamic, real-time adaptability and adjustment capabilities. Based on this, the following propositions are proposed:

P6 (Mechanism Proposition):AI-enabled process automation, dynamic resource scheduling, and digital-twin simulation significantly enhance the micro-foundations of organizational reconfiguring by enabling faster, lower-cost, and lower-risk resource adjustment, thereby improving firms' adaptability in rapidly changing environments.

Logic: From Experience-Based to Data-Driven Hybrid Logic

The final micro-foundation is logic, which is the underlying thought structure of how agents make judgments and take actions based on mechanisms. Traditional dynamic capability logic is built on human experience, heuristics, intuition, and analogical reasoning (Gavetti, 2012). The emergence of AI has created a new logical system, including statistical logic, optimization logic, and reinforcement learning logic. Therefore, this study proposes Hybrid Decision Logic for Dynamic Capabilities.

(1) Traditional Logic: Heuristic and Intuition-Driven. Traditional logic relies on managers' analogical reasoning, heuristics, strategic intuition, and social judgment. However, this type of logic is flexible but easily affected by subjective experience bias, personal emotions, and overconfidence, and has problems such as inaccuracy, unreliability, uncertainty, and difficulty in reproduction.

(2) AI Logic: Statistical, Optimization, and Reinforcement Learning. The logical systems of AI are completely different. First, there is Statistical Logic, which judges trends based on probability inference and regression coefficients, rather than "intuition"; second, there is Optimization Logic, which finds the optimal solution through objective functions and constraints; and third, there is Reinforcement Learning Logic, which learns the optimal strategy through trial and error and reward mechanisms, and is an important logic for enterprises to explore the unknown. These logics compensate for the limitations of human cognition, making decisions more accurate, consistent, and systematic.

(3) Hybrid Logic: Formed through the synergy of human experience and AI's mathematical reasoning. The core idea of Hybrid Logic is that neither humans nor AI alone can produce superior dynamic capabilities; the advantage arises from their complementary logics.

Specifically, firstly, in sensing: AI provides patterns, and humans provide meaning-making; secondly, in seizing: AI provides optimization decisions, and humans provide ethical boundaries, contextual judgments, and decision-making judgments; and thirdly, in reconfiguring: AI provides resource simulation, and humans provide decision-making judgments, organizational politics, and the ability to coordinate actions. This means that the logic of dynamic capabilities has been upgraded from "managerial judgment" to "human-machine collaborative judgment."

Based on the above inferences, the following propositions are put forward:
P7 (Boundary Proposition) : Dynamic capabilities are strengthened when firms integrate experience-based managerial heuristics with data-driven AI logics, forming a hybrid decision logic that improves interpretive depth and decision precision.
Based on the above, the following comprehensive proposition is proposed:
P8 (Integrative Proposition): Organizations that effectively align hybrid agency (Actor), algorithmic processes (Mechanism), and hybrid logic (Logic) will exhibit superior dynamic capabilities outcomes, including more accurate sensing, faster seizing, and more adaptive reconfiguring, and enhance the competitive advantage of the enterprises.

Methods

In order to reconstruct the micro-foundations of dynamic capabilities (DC) in the era of artificial intelligence, this study integrates several theoretical streams using a conceptual theory-building methodology. The method emphasizes theoretical generalizability and explanatory clarity by adhering to the conceptual development principles of MacInnis (2011), Gilson & Goldberg (2015） and Jaakkola (2020) rather than depending on empirical data. Redefining the fundamental elements of DC micro-foundations (actor, mechanism, logic), integrating AI-related mechanisms like algorithmic agency, hybrid intelligence, and organizational information processing, and creating a Hybrid Human–AI Dynamic Capabilities Framework that describes how AI transforms sensing, seizing, and reconfiguring are the three objectives of the research design.

The study focuses on high-impact research in DC, AI, decision-making, and human–AI collaboration and draws from theoretical literature found through systematic searches in Scopus and Web of Science. Thirty of the roughly 200 articles that were screened were included in the final theoretical integration. Finding conceptual inconsistencies in current DC and AI research, combining knowledge from DC, OIP, HCI, and algorithmic agency theories, and developing a cohesive model with eight propositions that explains how AI reconstructs capability formation processes are the three steps of the analytical strategy's synthesis logic. This approach prioritizes explanatory depth over empirical breadth, making it particularly suitable for theorizing emerging phenomena where constructs and causal mechanisms are still fluid.

Findings

According to this study, capability formation is moving from a human-centered, cognition-driven model to a hybrid human–AI paradigm as artificial intelligence methodically reconstructs the micro-foundations of dynamic capabilities (DC). The study suggests a three-part micro-foundation framework—Hybrid Actor, Algorithmic Mechanism, and Hybrid Logic—by combining DC, organizational information processing, algorithmic agency, and hybrid intelligence theories. AI first appears as a new organizational actor that collaborates with managers on tasks like sensing, seizing, and reconfiguring. AI increases the scope of sensing, improves the accuracy of strategic decisions, and speeds up resource reconfiguration through automation and digital twins through pattern recognition, anomaly detection, and simulation. Second, AI introduces algorithmic micro-foundations that work in tandem with human cognition. Continuous optimization beyond experiential reasoning is made possible by machine learning and reinforcement learning. Third, capability formation increasingly follows hybrid logic, combining managerial intuition with AI-driven prediction and optimization. Overall, the findings position AI as an emerging meta-capability that reshapes how organizations perceive, decide, and transform, offering a new theoretical lens for understanding capability evolution in the digital age.

Discussion and Conclusion

Rather than rejecting the foundational insights of dynamic capabilities theory, this study reconceptualizes its micro-foundations by incorporating algorithmic agency and hybrid decision logic.In order to address the fundamental question of "how the micro-foundations of dynamic capabilities are reconstructed in the era of artificial intelligence," this study suggests a novel framework for dynamic capabilities made up of hybrid actors, algorithmic mechanisms, and hybrid logic. The findings demonstrate that artificial intelligence (AI) is no longer just an exogenous technological resource but is progressively developing into an endogenous driving force for organizational capability building, radically altering how businesses perceive, seize, and reconfigure, and advancing dynamic capabilities from a "human-centric model" to a "human-machine hybrid model." This discovery has important ramifications for theories of human-machine collaboration, organizational information processing, and dynamic capability.

First, a significant addition to conventional dynamic capability theory is suggested by this study.The traditional DC (Dynamic Capabilities) framework relies on the judgment, experience, and intelligence of managers. However, this study shows that AI is starting to play a significant role in organizational decision-making and action in complicated and quickly evolving digital environments. AI greatly outperforms previous capabilities that depended on human cognition in terms of execution speed, accuracy, and scope through automated perception, prediction, and simulation capabilities. Future dynamic capabilities must therefore be seen as a "hybrid capability" , bolstered by both AI's algorithmic advantages and human strategic judgment.

Second, this study's framework contributes to the paradigm shift in the study of the "micro-foundations" of dynamic capabilities. Previous studies on the microfoundations of dynamic capabilities have mostly concentrated on organizational norms and managers' thought processes. However, this study shows that algorithmic mechanisms themselves can also function as the microfoundations of dynamic capabilities, using machine learning, deep learning, and reinforcement learning to continuously update organizational behavior patterns. In the digital age, this offers a fresh theoretical approach to comprehending the generative logic of organizational behavioral capabilities.

Third, this study provides valuable business practice insights. Developing dynamic capabilities no longer depends only on organizational learning and managerial experience for businesses in a crucial stage of digital transformation but requires the systematic construction of AI-integrated perception, decision-making, and restructuring systems. A company's competitive advantage will depend on its capabilities in human-machine collaboration, data infrastructure development, and algorithm governance.

In conclusion, the "human-machine hybrid dynamic capability framework" put forth in this study serves as a crucial basis for further empirical research in addition to meeting the practical requirements of dynamic capability reconstruction in the digital age. The differential mechanisms of human-machine hybrid dynamic capabilities under various nations, industries, organizational sizes, and technological maturity levels can be further explored in future research, and case studies and quantitative research can be used to validate the claims made in this paper. This study offers a fresh theoretical viewpoint for comprehending how businesses change in the AI era. While competitive advantage is theorized as an ultimate outcome, empirical validation remains for future research.

Theoretical Implications

The Dynamic Capabilities (DC) theory and the theoretical positioning of artificial intelligence in organizations both benefit from this study's numerous theoretical insights. The "human-centric" premise of conventional DC theory is first expanded upon. While this study suggests that AI participates not only as a technological tool but also as a new capability agent in sensing, seizing, and reconfiguring, the traditional DC（Dynamic Capabilities)framework highlights the crucial role of managerial cognition, experience, and judgment in capability formation. With this viewpoint, DC enters a new phase of "hybrid dynamic capabilities."

Second, this study offers a new foundation for future investigations into the microfoundations of digital enterprises. While cognition, routines, and organizational learning are the main components of traditional micro-foundations, this study suggests that algorithmic mechanisms can also be a basic source of capabilities. "Algorithmic microfoundations" are essential to comprehending the development of enterprise capabilities in the digital age because algorithmic processes like machine learning, deep learning, and reinforcement learning can constantly change to create new behavioral patterns.

Third, the integrative role of AI theory in strategic research is reinforced by this study. This study suggests that AI is a "meta-capability" that can improve or change the underlying logic of capability generation by integrating algorithmic agency, hybrid intelligence, and organizational information processing (OIP) theories into a dynamic capability framework. This offers a methodical theoretical framework for upcoming studies examining the relationship between DC and AI.

Practical and Social Implications

This study's "Human-Machine Hybrid Dynamic Capability Framework" has important ramifications for business operations. First, developing dynamic capabilities for businesses in a crucial phase of digital and intelligent transformation requires upgrading AI-related perception, decision-making, and resource reconfiguration systems concurrently with managerial experience, organizational norms, and learning mechanisms. Enterprises can improve their capabilities at every stage of sensing, seizing, and reconfiguring thanks to this research's framework, which offers a clear path from data infrastructure construction to algorithm application and finally to human-machine collaborative process design.

Second, this study shows that managers' roles are being redefined rather than eliminated in the AI era. The traditional role of "decision-makers" will give way to that of "human-AI orchestrators" , who will be in charge of creating data ecosystems, choosing algorithms, establishing boundary conditions, and monitoring model output. As a result, organizations must methodically enhance managers' critical thinking skills, algorithm comprehension, and data literacy.

Third, this study provides insights into societal policy design and AI governance. The transparency, fairness, and explainability of algorithms become critical factors influencing corporate capabilities and societal trust as AI becomes more integrated into fundamental organizational processes. To ensure a balance between capability upgrades and social value, policymakers should encourage businesses to develop responsible AI governance mechanisms.

Limitations and Suggestions for Future Research

Although this study provides a thorough conceptual framework for hybrid dynamic capabilities, several limitations point to potential areas for further investigation. First, the framework has not yet received empirical validation because it is a theory-building paper. To test how AI affects sensing, seizing, and reconfiguring in practice, future research should use case studies, surveys, experiments, or longitudinal designs. Second, the study treats AI broadly, but different types of AI—predictive, generative, reinforcement learning, or collaborative systems—may vary in their contributions to capability formation. Deeper understanding of these varied effects would be possible through comparative research across AI types, technological maturity levels, and industry contexts. Third, even though the paper presents "algorithmic microfoundations", more research is necessary to understand their internal workings and interactions with human microfoundations, especially with regard to data quality, model bias, managerial values, and organizational culture.

Furthermore, the suggested hybrid logic has not yet been systematically observed or measured; future research may create new metrics to measure how managers combine data-driven reasoning with intuition. Lastly, a thorough investigation is necessary to address potential risks such as algorithmic bias, opacity, organizational dependence, and power shifts. A more thorough theory of dynamic capabilities in the AI era will be developed by examining both the augmenting and distorting effects of AI.

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