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Competitive Actions in the Age of AI Agents: a Framework for Strategy Formulation Under Conditions of Technological Disruption

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ABSTRACT

Strategy formulation theory in engineering management has long rested on a foundational premise: that competitive actions are initiated, executed, and responded to by human decision-makers operating within human cognitive limits and institutional time horizons. Organizations across engineering management sub-fields are now deploying AI agentic systems capable of executing competitive moves autonomously, continuously, and at speeds that human-led processes were never designed to match. The result is a competitive environment in which the speed of rivalry, strategic positioning, and organizational conditions for advantage have materially shifted — while the theoretical frameworks guiding strategy formulation have not.

Keywords: *AI agents, strategy formulation, engineering management, algorithmic motivation, dynamic capabilities*

INTRODUCTION

Competitive strategy theory has been built across six decades on one foundational assumption: that firms are directed by human strategists who perceive rivals, decide how to act, and execute competitive moves through human-led processes. Porter's (1980, 1985) generic strategy typology assumes human decision-makers choosing and sustaining competitive positions. Chen's (1996) AMC Framework assumes human awareness of competitive stimuli, human motivation to act, and human-led capability deployment. Teece, Pisano, and Shuen's (1997) Dynamic Capabilities framework assumes human managers sensing, seizing, and reconfiguring resources. The competitive actor in strategy theory has always been human. That assumption is now being structurally dismantled.

AI agentic systems — autonomous architectures that perceive competitive environments, reason across multi-step sequences, and execute actions without continuous human authorization — are operating inside engineering management organizations at a scale and velocity that existing frameworks were not designed to explain. Unlike enterprise software that preceded them, AI agents are not decision support systems — they are decision-making systems. When AI agents execute competitive actions autonomously, they become strategic actors, and the frameworks built to explain human competitive behavior require fundamental reconceptualization.

The scale of AI agentic adoption is substantial and accelerating. MIT Sloan Management Review and Boston Consulting Group (2025) found that 35 percent of organizations had adopted AI agents by 2023, with 44 percent planning near-term deployment. Deloitte (2026), based on 3,235 senior leaders across 24 countries, confirms that despite this velocity, more than 80 percent of organizations are not yet seeing material contribution from AI investments — a systematic mismatch between AI agent deployment and strategy formulation readiness. Engineering Management sits at the convergence of engineering and management sciences, encompassing technology management, project management, systems engineering, innovation management, infrastructure governance, and digital transformation. Across all sub-fields, the theoretical question is the same: how must strategy formulation frameworks be reconceived when AI agents — not human managers alone — are executing competitive actions?

Objectives of the Study

General Objective: This study aims to identify the theoretical gaps in existing strategy formulation and competitive dynamics frameworks as applied to organizations deploying AI agentic workforces across engineering management sub-fields, and to propose the CA3 Framework specifying how strategy formulation must evolve under AI agentic competitive conditions.

Specific Objectives:

- To examine and critically evaluate three validated instruments — the SCC Scale, the AMC Framework, and the Cisco AI Readiness Assessment — for their applicability and limitations under AI agentic workforce conditions.
- To conduct an in-depth analysis of four literature bodies: strategy formulation under AI conditions, competitive dynamics and AI agents, the AI agentic workforce literature, and technological disruption and competitive positioning.
- To formally identify the theoretical gaps in existing frameworks as applied to engineering management organizations deploying AI agentic workforces.
- To propose the CA3 Framework as a theoretical contribution specifying how strategy formulation must be reconceptualized when AI agents become active participants in competitive action execution.

Significance of the Study

For engineering management practitioners — technology managers, project directors, infrastructure leaders, and digital transformation executives — this study provides the first theoretically grounded framework specifying how strategy formulation must evolve when AI agents execute competitive actions autonomously. For the academic research community, this study extends the AMC Framework, Dynamic Capabilities theory, and Porter's generic strategy typology to account for AI agents as competitive actors, formally identifying three research gaps constituting an agenda for empirical validation. For organizations across engineering management sub-fields, this study establishes the theoretical foundation for connecting AI agent deployment decisions to competitive strategy outcomes rather than treating AI adoption as a technology problem divorced from strategy formulation.

METHODS

Research Design

This study employs an In-Depth Literature Analysis — A non-empirical design derives theoretical contributions from the systematic examination of existing published literature, requiring no fieldwork, respondents, or ethical clearance. The design is evaluated on the depth, rigor, and theoretical coherence of the literature synthesis and the theoretical contribution it produces.

Literature Search Strategy

The literature search was conducted across six primary databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, MDPI, and Google Scholar. IEEE Xplore was included specifically to capture engineering management and technology management literature. Search strings combined terms from three conceptual domains: (1) strategy formulation, competitive dynamics, competitive actions, competitive strategy, generic strategies, AMC Framework, dynamic capabilities; (2) AI agents, agentic AI, autonomous AI systems, algorithmic competitive action, AI workforce deployment, agentic AI governance; and (3) engineering management, technology management, project management, infrastructure governance, digital transformation, organizational AI readiness. Boolean operators (AND, OR) were applied across domains. The temporal scope covers 2018 to 2026, with emphasis on 2022–2026 publications reflecting the rapid evolution of agentic AI capabilities. Foundational theoretical works published before 2018 — Porter (1980, 1985), Chen (1996), Teece et al. (1997), Barney (1991), Christensen (1997) — were included based on theoretical centrality regardless of publication date.

Rural Farm Schools and Experiential Agricultural Education

Rural Farm Schools connect classroom instruction with practical agricultural learning. Their relevance is consistent with the Rural Farm Schools Act of 2013 and its implementing rules, which recognize the need for an alternative delivery mode responsive to the conditions of rural communities (Republic Act No. 10618, 2013; Department of Education, 2015). Farm-based learning may develop agricultural knowledge, environmental awareness, and practical decision-making. A systematic review by Pflugh Prescott et al. (2020) found that farm-to-school activities can support student-related outcomes, while Goldman and Alkaher (2024) emphasized the role of farm schools in environmental and sustainability education.

Rural Livelihoods and Student Context

Students' experiences of rural education are shaped by household conditions. Rural families frequently combine agricultural labor with fishing, construction, transportation services, and small enterprises to manage income variability. Ellis (2000) described livelihood diversification as a central rural strategy, while Briones (2020) characterized agricultural employment and household conditions in selected Philippine provinces. These conditions are relevant because access to resources, food security, and livelihood stability may influence students' participation in practical learning activities.

Implementation Requirements and Sustainability

Successful agricultural education depends on adequate resources, trained educators, institutional support, and community partnerships. FAO (2020) identified agricultural education and training as important mechanisms for empowering rural youth. UNESCO (2020) likewise emphasized the need for educational programs that are locally responsive and sustainable. Contemporary studies have also highlighted the value of agricultural learning for environmental citizenship and the potential of technology-supported extension approaches for farming communities (Goldman & Alkaher, 2024; Santiago & Navarro, 2025).

Research Gap

Policy discussions commonly describe the goals of rural agricultural education, but student-centered evidence on day-to-day implementation remains limited. Assessing students' perceptions can reveal which constraints most directly affect learning and which opportunities remain valuable despite resource limitations. This study addressed that gap within the specific context of Mahinog National High School.

RESULTS AND DISCUSSION

Validated Instruments and Their Limitations Under AI Agentic Conditions

Three validated strategy formulation and competitive dynamics instruments were examined as the theoretical reference baseline for this study. Each instrument was assessed for its definition, validation rigor,

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documented applications in engineering management and strategic management literature, and specific limitations under AI agentic workforce conditions. The unifying logic across all three instruments is deliberate: each was developed to explain how human organizations formulate strategy and execute competitive actions — and each fails, in a specific and theoretically significant way, to account for the conditions created when AI agents become active participants in the competitive action sequence.

1. *Strategic Change Capability (Scc) Scale*

Dimension	Description
Authors	Bekos, Chari, Jaakkola & Evanschitzky (2025) | Journal of Marketing | Scopus Q1
Type	Validated psychometric scale — 6-phase development: Item Generation → EFA → CFA → Nomological Validity → Cross-Industry Generalizability
Construct	Strategy formulation capability — organizational ability to plan and enact strategic change through five sequential dimensions
Limitation	No agentic AI dimension; validated in marketing contexts only — not tested in engineering management organizations

The SCC Scale is the most recently validated instrument for measuring strategy formulation capability. Bekos et al. (2025) define SCC as a multidimensional dynamic capability enabling firms to enact strategic changes in light of new threats and opportunities — distinguishing between planning and enacting strategic change through five sequential dimensions: establishing the business case, preparing employees, setting up the organization, institutionalizing change behaviors, and assessing and adjusting. Despite its rigor, the SCC Scale carries a foundational limitation: all validation studies were conducted in marketing organization contexts and the scale contains no dimension addressing the governance, oversight, or strategic alignment of AI agentic systems as strategy execution mechanisms.

Nilo, Dungca, Mallari, and Florencondia (2025) document structural differences in how strategy formulation responsibilities are distributed between formal leaders and institutional processes in Philippine public sector and academic engineering management contexts — a pattern that agentic AI deployment will further complicate as algorithmic systems absorb functions previously held by human organizational actors. Balagtas and Mallari (2025), examining digital leadership and water resource management efficiency in the NIA-UPRIIS Division II, found that the absence of a structured digital leadership framework directly limits an organization's ability to translate technology deployment into strategic outcomes — mapping onto the SCC Scale's Dimension 1 and Dimension 3 limitations in AI agentic environments.

2. *Awareness-Motivation-Capability (AMC) Framework*

Dimension	Description
Authors	Chen (1996); Chen & Miller (2007, 2012) | AMR, AMJ, AMA — all Scopus Q1
Type	Foundational theoretical framework — empirically validated across 5+ major domains including 4,033-firm longitudinal panel (Zhang & Tan, 2024)
Construct	Competitive dynamics — explains when, why, and how firms initiate or respond to competitive actions through three multiplicative conditions
Limitation	Foundational human-actor assumption — AI agents possess functional analogs to all three constructs without human cognitive or institutional constraints

The AMC Framework is the dominant theoretical model for competitive action research globally. Chen (1996) posits that competitive action occurs only when three conditions are jointly satisfied: Awareness — the firm perceives and recognizes the competitive stimulus; Motivation — the firm has sufficient incentive to act; and Capability — the firm possesses the resources necessary to execute the competitive move. Grounded in Schumpeterian and Austrian economics, the AMC Framework transformed competitive dynamics from structural analysis into behavioral analysis — explaining not just where firms compete but how they actually compete. Zhang and Tan (2024), in a landmark longitudinal study covering 4,033 listed Chinese companies from 2007 to 2021 published in Technological Forecasting and Social Change, confirmed AMC's validity as an explanatory framework for strategic responses to technological disruption — the most current and directly applicable large-scale empirical validation.

The AMC Framework's most fundamental limitation for AI agentic competitive environments is its foundational assumption that Awareness, Motivation, and Capability are properties of human decision-makers with cognitive and institutional constraints. AI agents possess functional analogs to all three constructs — continuous environmental scanning (Awareness), encoded objective functions (Motivation), and pre-trained competencies with tool access (Capability) — without the same constraints. The framework does not explain competitive dynamics in which AI agents initiate, execute, or respond to competitive actions without human authorization for each action. This is the most critical theoretical gap the CA3 Framework addresses.

3. *Cisco Ai Readiness Assessment*

Dimension	Description
Source	Cisco Systems (2025) — Third Annual Global Study | 8,000+ leaders | 30 markets | 26 industries
Type	Organizational-level evaluation framework — six-pillar structural readiness assessment
Construct	Organizational AI readiness — structural preparedness for AI agent deployment and competitive value realization across six simultaneous pillars
Limitation	Measures general AI adoption readiness — does not connect readiness profiles to competitive action theory or differentiate agentic AI from conventional AI adoption

The Cisco AI Readiness Assessment is the most comprehensive organizational-level AI readiness instrument identified in this review. Cisco (2025) defines readiness as a system-level property across six pillars — Strategy, Infrastructure, Data, Governance, Talent, and Culture — where weakness in any single pillar limits competitive AI value regardless of strength on the others. Only 13 percent of organizations globally are fully AI-ready across all six pillars. Dwivedi et al. (2021), in a multidisciplinary AI research agenda across 50 scholars published in the International Journal of Information Management, independently confirmed that strategy alignment, data governance, and human capital are the three most critical determinants of AI value realization — mapping precisely to Cisco's Strategy, Data, and Talent pillars. The Assessment carries three specific limitations: it does not differentiate agentic AI from conventional AI adoption; it does not connect readiness profiles to competitive action theory; and it has not been validated for engineering management contexts where professional accountability, regulatory constraints, and project-based structures create distinct readiness conditions.

Unified Gap Across All Three Instruments

While existing literature has produced a validated strategy formulation capability instrument (Bekos et al., 2025), a well-theorized framework for competitive dynamics (Chen, 1996; Teece et al., 1997), and a practitioner-validated assessment of organizational AI readiness (Cisco, 2025), no validated instrument or theoretical framework simultaneously addresses how organizations operating across engineering management sub-fields can formulate strategy and execute competitive actions under AI agentic workforce conditions — where AI agents function as autonomous competitive actors rather than as strategic support tools.

Three specific theoretical gaps are formally identified: (1) The AMC Human-Actor Gap — the AMC Framework attributes Awareness, Motivation, and Capability to human decision-makers, but AI agents possess functional analogs to all three without human cognitive or institutional constraints, compressing competitive action cycles and introducing algorithmic motivation as an untheorized construct; (2) The Generic Strategy Collapse Gap — Porter's generic strategy typology assumes human-paced deliberate positioning decisions, but AI agents can simultaneously execute Cost Leadership optimization, Differentiation personalization, and Focus micro-targeting

— collapsing the theoretical boundaries between strategic positions; and (3) The Readiness-Action Disconnection Gap — organizational readiness instruments measure AI adoption preparedness broadly but do not connect readiness profiles to competitive action theory, do not differentiate agentic AI from conventional AI, and have not been validated for engineering management contexts.

Literature Review

Strategy Formulation Under AI Conditions: The Human-Centered Baseline

The strategy formulation literature originates with Ansoff (1965) and Andrews (1971), who established strategy as a formal process of organizational goal-setting and resource alignment. Mintzberg (1994) challenged this deliberate planning model, demonstrating that strategy is as much emergent as deliberate — a pattern of decisions rather than a formal plan. This carries profound implications for AI agentic competitive conditions: if strategy emerges from patterns of decisions, and AI agents execute thousands of micro-decisions daily on behalf of an organization, agentic systems may be generating emergent strategies without explicit managerial authorization. Porter's (1980, 1985) generic strategy framework formalized strategy formulation around three competitive positions: Cost Leadership, Differentiation, and Focus. Islami, Mustafa, and Topuzovska Latkovikj (2020) confirmed that generic strategy alignment remains a significant predictor of firm performance across 151 manufacturing and service firms. However, Jafari et al. (2025) demonstrate that AI-driven real-time competitive analysis fundamentally challenges the boundaries of Porter's three positions — AI agents can simultaneously optimize for cost efficiency, personalize customer experiences, and micro-target specific market segments, rendering the three-strategy typology insufficient for AI-augmented competitive environments. The SCC Scale (Bekos et al., 2025) provides the most current validated strategy formulation capability instrument but does not address how the strategy formulation responsibility boundary between humans and AI agents should be theorized.

Competitive Dynamics and AI Agents: The Disruptive Competitive Condition

The competitive dynamics literature — anchored in Chen (1996) and extended by Chen and Miller (2012) — establishes competitive action and response as the primary unit of strategic analysis. Zhang and Tan's (2024) landmark longitudinal study of 4,033 Chinese firms confirmed AMC's validity as an explanatory framework for strategic responses to technological change. The Dynamic Capabilities perspective (Teece et al., 1997; Teece, 2007, 2025) complements AMC's competitive action focus: where AMC explains when and why firms act competitively, Dynamic Capabilities explains how firms build, deploy, and reconfigure capabilities that make competitive action possible and sustainable. De la Torre and De la Vega (2025), validated through SEM across 216 technology companies, confirmed that dynamic capabilities directly mediate the relationship between AI adoption and competitive performance. The 2026 Wisvora extension — 'From VRIN to Velocity' — proposes that AI-accelerated markets require a fifth competitive resource property: Velocity, defined as the speed at which the firm can deploy, reconfigure, and scale AI agents relative to rivals. Corroborating this trajectory from a parallel domain, Oganiza, Mallari, and Arboleda (2026), in the Human-to-Algorithmic Leadership Transition (HALT) Framework, documented that existing strategic leadership frameworks — including Dynamic Managerial Capabilities (Helfat & Martin, 2015) and Upper Echelons Theory (Hambrick & Mason, 1984) — exhibit structurally identical gaps to those identified in competitive dynamics theory: both leadership and competitive dynamics literatures were developed for human-directed environments and require systematic extension when AI agents autonomously perform organizational functions. This convergence across parallel theoretical domains strengthens the necessity of the CA3 Framework's reconceptualization agenda.

The AI Agentic Workforce Literature: The Empirical Deployment Context

Tejada-Ortigiosa et al. (2025), in Information Fusion (Scopus Q1), provide the first formal peer-reviewed distinction between AI Agents — modular, task-specific systems for single-task automation — and Agentic AI — complex, multi-agent systems in which specialized agents collaboratively decompose goals, communicate, and coordinate toward shared objectives across dynamic operational boundaries. This distinction is not semantic: AI Agents are tools; Agentic AI systems are competitive actors. McKinsey's Agentic Organization Model (Sukharevsky et al., 2025) identifies five organizational pillars required for agentic AI to deliver competitive value: Business Model, Operating Model, Governance, Workforce and Culture, and Technology and Data. The MDPI systematic review on agentic AI frameworks in SMEs (2025), applying PRISMA 2020 methodology across 66 studies, identified that the most critical unresolved challenge in organizational agentic AI deployment is the absence of validated frameworks for connecting agent-level operational decisions to organizational-level competitive strategy — directly supporting this study's theoretical contribution. Deloitte (2026) corroborated this, reporting that 42 percent of organizations have no formal agentic AI strategy.

Technological Disruption and Competitive Positioning: Resource and Positioning Theory Extensions

Christensen's (1997) Disruptive Innovation Theory establishes the competitive mechanism through which AI agents are reshaping industry structures. Agentic AI exhibits the classic disruptive trajectory: entering at the low end of competitive action — basic task automation — then rapidly improving to execute complex multi-step strategy formulation. Bower and Christensen (1995) identified conditions under which incumbents consistently fail to respond to disruptive technologies — conditions structurally present in engineering management organizations built around human-led strategy formulation. Schmidt and Druehl (2008), in a Scopus Q1 study, firmly classify agentic AI in the disruptive category for most engineering management contexts.

Barney's (1991) VRIN framework and the Wisvora (2026) Velocity extension address the core resource question: when AI agents execute competitive actions, what constitutes the firm's durable competitive advantage? The answer is that the AI agent system itself is not the durable resource — it is imitable and subject to rapid obsolescence. The durable competitive resource is the organizational capability to orchestrate, govern, and continuously improve AI agents faster than rivals, integrating Dynamic Capabilities' reconfiguration construct with Barney's VRIN logic and the AMC Framework's capability construct.

The CA3 Framework: Proposed Theoretical Contribution

The Competitive Actions in the Age of AI Agents (CA3) Framework is proposed as the theoretical contribution of this study. The CA3 Framework does not replace existing theory — it specifies the extensions required when AI agents become active participants in the competitive action sequence. The framework transitions the unit of competitive analysis from the human decision-maker to the human-AI competitive team, from human-paced AMC cycles to machine-speed algorithmic competitive action, and from deliberate generic strategy positioning to dynamic AI-mediated competitive configuration. The framework is grounded in four propositions derived from the synthesis of the four literature bodies examined.

Proposition 1: Reconceptualization of AMC Constructs Under Agentic Conditions. The AMC Framework's three constructs must be reconceptualized when AI agents become competitive actors. Awareness transitions from a human cognitive construct to a continuous, machine-speed environmental scanning function executed across multiple competitive signals simultaneously. Motivation transitions from a human psychological construct shaped by competitive tension to a parameterized algorithmic priority function encoded in the AI agent's objective architecture and calibrated by human strategists. Capability transitions from a stock of human and technological resources to a composite of human orchestration capability and AI agent execution capability — where AI-amplified capability asymmetry becomes the primary determinant of competitive action timing and scale. Engineering management organizations must assess, develop, and govern these three reconceptualized constructs as a unified competitive intelligence architecture.

Proposition 2: Generic Strategy Position Fluidity Under AI Agentic Execution. Porter's three generic strategy positions — Cost Leadership, Differentiation, and Focus — were theorized as mutually exclusive because human decision-makers cannot simultaneously optimize for cost efficiency, customer personalization, and segment specificity. AI agents dissolve this constraint: they can simultaneously execute cost optimization (Cost Leadership), personalization engines (Differentiation), and micro-segment targeting protocols (Focus) within the same competitive action cycle. Engineering management organizations must reconceptualize strategy formulation not as

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a choice between positions but as a governance architecture problem — determining which AI agents are authorized to execute which strategic behaviors, at what speed, with what accountability, and subject to what human override conditions.

Proposition 3: Readiness-to-Action Translation as a Strategy Formulation Requirement. Organizational AI readiness must be explicitly translated into competitive action theory for engineering management organizations to realize strategic value from AI agentic deployment. The CA3 Framework proposes that each Cisco readiness pillar maps to a specific competitive action failure mode: a Strategy pillar gap produces AI agents executing actions misaligned with strategic intent; an Infrastructure gap limits competitive action speed and scale; a Data gap produces incomplete AMC Awareness; a Governance gap produces unauthorized competitive actions without accountability; a Talent gap produces strategy teams unable to orchestrate or recalibrate AI agent behaviors; and a Culture gap produces institutional resistance preventing readiness investments from translating into competitive action capability. Balagtas and Mallari (2025), in the NIA-UPRIIS Division II case study, demonstrated that infrastructure governance organizations face measurable performance gaps when digital leadership capability is not explicitly connected to strategic technology deployment outcomes — precisely the Strategy-to-Infrastructure pillar gap that Proposition 3 formalizes.

Proposition 4: AI Agent Orchestration Capability as the Durable Competitive Resource. The CA3 Framework proposes that the durable source of competitive advantage in engineering management organizations is not the AI agent system itself — it is imitable, commercially available, and subject to rapid obsolescence — but the organizational capability to orchestrate, govern, and continuously improve AI agents faster than rivals. This AI Agent Orchestration Capability (AAOC) integrates Dynamic Capabilities' sensing, seizing, and reconfiguring functions applied to the AI agent portfolio; the AMC Framework's capability construct extended to encompass AI execution capacity alongside human strategic judgment; and Barney's (1991) VRIN criteria applied to orchestration knowledge — which is valuable, rare, costly to imitate, and non-substitutable by the AI agents it governs. Organizations that develop superior AAOC will sustain competitive advantage regardless of which AI agent systems their rivals deploy.

Summary of Findings

This study conducted an In-Depth Literature Analysis examining theoretical gaps in existing strategy formulation and competitive dynamics frameworks as applied to engineering management organizations deploying AI agentic workforces, and proposed the CA3 Framework to address those gaps.

A. On Validated Instruments. The SCC Scale (Bekos et al., 2025) measures human organizational strategy change capability with no dimension addressing AI agent governance or agentic strategy execution. The AMC Framework (Chen, 1996) rests on a human-actor assumption that AI agents functionally dissolve — possessing analogs to Awareness, Motivation, and Capability without human cognitive constraints. The Cisco AI Readiness Assessment (2025) measures broad organizational AI adoption readiness without connecting readiness profiles to competitive action theory, differentiating agentic AI from conventional AI adoption, or addressing engineering management context specificity.

B. On Strategy Formulation and Competitive Dynamics. The foundational literature establishes a theoretically robust but AI-incomplete baseline. Jafari et al. (2025) confirm AI-driven analysis challenges Porter's three-strategy typology for AI-augmented environments. Zhang and Tan (2024) confirm AMC's applicability to technology disruption contexts. De la Torre and De la Vega (2025) confirm dynamic capabilities mediate between AI adoption and competitive performance. Oganiza, Mallari, and Arboleda (2026) confirm that parallel leadership theory faces identical human-actor gaps, strengthening the CA3 Framework's theoretical necessity.

C. On Agentic AI and Technological Disruption. Tejada-Ortigiosa et al. (2025) establish the AI Agents-as-tools versus Agentic AI-as-competitive-actors distinction as the theoretical boundary condition existing frameworks have not crossed. The MDPI systematic review (2025) confirms the absence of frameworks connecting agent-level decisions to organizational-level competitive strategy as the most critical unresolved challenge in agentic AI deployment. Christensen (1997) and the VRIN + Velocity synthesis collectively establish that the durable competitive resource under agentic conditions is organizational orchestration capability, not the AI system itself.

CONCLUSIONS

A. This study concludes that existing strategy formulation and competitive dynamics frameworks — the SCC Scale, the AMC Framework, and the Cisco AI Readiness Assessment — are theoretically insufficient for guiding competitive strategy formulation in engineering management organizations deploying AI agentic workforces. Each framework carries a specific and consequential theoretical gap at the precise point where AI agents enter the competitive action sequence.

B. The AMC Framework's human-actor assumption — the most foundational assumption in competitive dynamics theory — requires explicit reconceptualization under AI agentic conditions. Awareness, Motivation, and Capability as human cognitive and institutional constructs do not adequately explain competitive dynamics in which AI agents continuously scan competitive environments, execute encoded objective functions, and deploy pre-trained competencies at machine speed without human authorization for each action.

C. Porter's generic strategy typology requires theoretical extension under AI agentic conditions. The mutual exclusivity of Cost Leadership, Differentiation, and Focus — maintained in human-led competitive environments by cognitive and organizational constraints — is dissolved by AI agents capable of executing multiple strategic behaviors simultaneously. Engineering management organizations must reconceptualize strategy formulation under agentic conditions as a governance architecture problem rather than a strategic position selection problem.

D. The proposed Competitive Actions in the Age of AI Agents (CA3) Framework provides the first theoretically grounded architecture specifying how strategy formulation must evolve under AI agentic conditions — through four propositions addressing AMC reconceptualization, generic strategy fluidity, readiness-to-action translation, and AI agent orchestration capability as the durable competitive resource. The CA3 Framework extends existing competitive dynamics and strategy formulation theory rather than replacing it.

Recommendations

1. Future researchers are recommended to conduct empirical validation of the CA3 Framework's four propositions through quantitative survey-based studies targeting strategy formulation leaders — specifically technology managers, project directors, and digital transformation executives — across engineering management organizations deploying AI agentic workforces. The framework's propositions constitute testable hypotheses operationalizable through validated survey instruments and testable using structural equation modeling approaches.
2. Researchers in Engineering Management and Strategic Management are recommended to develop a validated measurement instrument assessing AI Agent Orchestration Capability (AAOC) — the durable competitive resource identified in CA3 Proposition 4. Such an instrument would measure an organization's ability to specify AI agent objectives, monitor agent outputs, recalibrate agent parameters, and terminate misaligned agent deployments — constituting a new competitive capability construct absent from existing validated instruments.
3. Engineering management organizations are recommended to apply the CA3 Framework's Proposition 3 — the readiness-to-action translation — as a competitive action audit framework, mapping their current Cisco AI Readiness Assessment pillar scores directly to specific competitive action capability gaps. This translation converts a general AI adoption diagnostic into a strategy formulation action plan aligned with the organization's competitive context.
4. Strategy formulation practitioners in engineering management sub-fields — technology management, project management, infrastructure governance, and digital transformation — are recommended to reconceptualize AI agent deployment decisions as competitive strategy decisions rather than technology procurement decisions. The CA3 Framework establishes that which AI agents are deployed, how their

objectives are specified, how their outputs are monitored, and how their parameters are recalibrated are all strategy formulation acts with direct competitive action consequences.

5. Future researchers are recommended to investigate the CA3 Framework's applicability across specific engineering management sub-fields — testing whether the four propositions hold equally across technology management, project management, infrastructure governance, and digital transformation contexts, or whether sub-field-specific modifications are required. Context-specific empirical validation would advance the framework from a general theoretical architecture to a field-tested strategy formulation tool for engineering management practitioners.

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