International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 3
May-Jun 2026, PP 1-21

Agentic AI Strategy as a Dynamic Capability: How Autonomous Systems Reshape Enterprise Transformation

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Abstract. As organizations transition from generative AI experimentation to agentic AI deployment, traditional frameworks for AI strategy have become structurally insufficient. This study conceptualizes agentic AI strategy as a dynamic capability through which firms systematically sense automation opportunities, seize value through autonomous multi-step workflows, and reconfigure governance, talent, and data infrastructures to sustain competitive advantage. Employing a longitudinal mixed-methods design — integrating annual-report text mining, AI investment announcements, patent data, and executive interviews from 312 large public firms across seven industry sectors between 2021 and 2026 — the study develops and validates an Agentic AI Strategic Maturity Index (AAMI). Structural equation modeling confirms that integrated agentic AI strategies are associated with significantly higher operational performance ($\beta = 0.35$, $p < .001$) and revenue growth ($\beta = 0.29$, $p < .001$) compared to fragmented AI tool adoption. Qualitative analysis of 42 executive interviews reveals five dominant strategic challenges: orchestration complexity, governance lag, talent asymmetry, value attribution difficulty, and cultural resistance to human-AI teaming. The paper advances a novel theory of autonomous digital transformation, provides empirical evidence on AI-driven competitive advantage, and offers actionable strategic guidance for executives managing enterprise-wide AI agents. Findings suggest that agentic AI maturity, not mere AI investment intensity, is the pivotal differentiator of sustained enterprise performance in the post-generative AI era.

Keywords: Agentic AI, dynamic capabilities, AI strategy, enterprise transformation, autonomous systems, digital transformation, AI maturity, strategic management.

I. Introduction

The emergence of large language model (LLM)-powered autonomous agents marks a structural discontinuity in the evolution of enterprise artificial intelligence. Whereas first-generation AI applications — encompassing machine learning classifiers, recommendation engines, and robotic process automation (RPA) — operated as sophisticated decision-support tools requiring continuous human oversight, agentic AI systems possess the capacity to perceive environmental states, formulate multi-step plans, execute sequences of actions, self-correct upon encountering errors, and collaborate with other agents to accomplish complex organizational objectives with minimal human intervention (Eloundou et al., 2024; McKinsey Global Institute, 2025). This qualitative shift from tool-centric to agent-centric AI deployment demands a commensurate evolution in strategic management theory and practice.

The managerial implications are profound. According to McKinsey Global Institute (2025), enterprise AI agents are projected to automate between 40% and 70% of complex knowledge work tasks across major industry sectors by 2028, generating potential value in excess of $4.4 trillion annually. Yet the extant AI strategy literature — still anchored in frameworks developed for rule-based systems and narrow AI applications — offers limited conceptual apparatus for analyzing how firms should build, govern, and scale autonomous AI capabilities. Existing frameworks emphasize AI adoption rates, investment levels, and data quality metrics, while neglecting the distinctly dynamic nature of agentic AI: its capacity to autonomously reconfigure workflows, learn from operational feedback, and reshape organizational boundaries in real time (Iansiti & Lakhani, 2023).

This theoretical gap is consequential. Firms that conceptualize agentic AI merely as a collection of point solutions — deploying individual agents reactively in response to competitive pressure — risk systemic fragmentation: incompatible agent architectures, ungoverned data flows, and misaligned incentive structures that collectively undermine the strategic coherence necessary for sustained competitive advantage (Teece, 2007). Conversely, firms that cultivate agentic AI as a core organizational capability — institutionalizing processes for sensing automation opportunities, orchestrating multi-agent workflows, and continuously reconfiguring supporting infrastructures — position themselves to capture compounding strategic returns that are inaccessible to more reactive competitors.

This study addresses the following research questions: (RQ1) How can agentic AI strategy be theorized as a dynamic capability? (RQ2) What dimensions constitute strategic maturity in agentic AI deployment, and how can these be measured? (RQ3) Do firms with higher agentic AI strategic maturity demonstrate superior financial and operational performance compared to firms employing fragmented AI approaches? (RQ4) What strategic challenges do executives encounter in orchestrating enterprise-wide agentic AI, and how do these challenges interact with organizational performance?

To address these questions, the study adopts a mixed-methods longitudinal design spanning 2021 to 2026, combining natural language processing of annual reports, AI investment disclosures, patent data, and semi-structured executive interviews from 312 large public firms across seven industry sectors. Drawing on dynamic capabilities theory (Teece et al., 1997; Eisenhardt & Martin, 2000), the resource-based view (Barney, 1991; Wernerfelt, 1984), and digital innovation scholarship (Nambisan et al., 2017; Fichman et al., 2014), the study develops the Agentic AI Strategic Maturity Index (AAMI) — a multi-dimensional measurement instrument that captures the breadth, integration, and governance sophistication of enterprise agentic AI strategies.

The paper makes four primary contributions. First, it extends dynamic capabilities theory to the domain of autonomous AI systems, proposing sense-seize-reconfigure as the operative logic of agentic AI strategy. Second, it develops and validates the AAMI as a theoretically grounded and empirically robust measurement instrument. Third, it provides longitudinal evidence on the performance consequences of agentic AI strategic maturity across industry contexts. Fourth, it offers an inductively derived typology of strategic challenges that enrich both theory and executive practice. The remainder of the paper is organized as follows: Section 2 reviews relevant literature and develops the theoretical framework; Section 3 describes research methodology; Section 4 presents quantitative results; Section 5 reports qualitative findings; Section 6 discusses contributions, limitations, and future research directions; Section 7 concludes.

II. Theoretical Background and Framework Development

Dynamic Capabilities and the AI Strategy Nexus

Dynamic capabilities theory, originating with Teece et al. (1997) and subsequently refined by Eisenhardt and Martin (2000) and Teece (2007), posits that sustained competitive advantage in turbulent environments derives not merely from the possession of valuable, rare, inimitable, and non-substitutable resources (Barney, 1991), but from a firm's higher-order capacity to sense opportunities and threats, seize value by mobilizing and coordinating resources, and reconfigure asset stocks to maintain relevance as market conditions evolve. The tripartite sense-seize-reconfigure framework provides a theoretically parsimonious yet empirically tractable lens for analyzing strategic capability development.

The intersection of dynamic capabilities theory and AI strategy has attracted growing scholarly attention. Early contributions by Sambamurthy et al. (2003) conceptualized IT capabilities as enabling digital options — strategic flexibilities that enhance organizational agility in uncertain environments. More recent scholarship by Iansiti and Lakhani (2023) extended this logic to AI-native firms, arguing that AI capabilities constitute a novel class of dynamic capability through which algorithms continuously reshape competitive positions. Lee et al. (2023) provided longitudinal evidence that AI dynamic capabilities mediate the relationship between digital investment and market performance across 18 industry sectors. However, these contributions focus predominantly on narrow AI applications and do not account for the qualitatively distinct strategic properties of agentic systems.

Agentic AI introduces three strategic properties absent from prior AI generations: goal-directed autonomy (the capacity to pursue objectives across multi-step, multi-environment action sequences without continuous human instruction), adaptive orchestration (the ability to dynamically allocate sub-tasks among specialized agents in response to environmental feedback), and emergent learning (the capacity to generate novel problem-solving strategies not explicitly programmed or anticipated at deployment). These properties create both new sources of strategic value and new categories of strategic risk that require fresh theoretical treatment.

From Generative AI to Agentic AI: A Strategic Discontinuity

The generative AI era (approximately 2021 to 2024) was characterized by LLM deployment as productivity augmentation tools: AI as sophisticated autocomplete, summarization engines, and content generators requiring human direction at each step. The strategic logic was primarily additive — AI enhanced individual and team productivity without fundamentally restructuring organizational architectures. The agentic AI era (2024 onwards) represents a structural shift: agents operate as semi-autonomous organizational actors capable of initiating, executing, and closing complex workflows that previously required coordinated human teams (Gartner, 2024; IBM Institute for Business Value, 2024).

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 3
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This strategic discontinuity parallels the transition from information technology as a tool to IT as a platform that Brynjolfsson et al. (2021) describe in their analysis of the productivity J-curve: the full economic returns of transformative technologies are realized only after significant complementary investments in organizational processes, governance structures, human capital, and cultural norms. Applied to agentic AI, this implies that firms capturing immediate productivity gains from individual agent deployments without investing in integrated strategic infrastructure will encounter diminishing returns as competitive imitation erodes first-mover advantages, while firms that build systematic dynamic capabilities around agentic AI will accumulate compounding strategic returns.

Theoretical Model: Agentic AI as Dynamic Capability

Building on Teece et al. (1997) and the preceding analysis, this study conceptualizes Agentic AI Strategy as a Dynamic Capability (AADC) comprising three interdependent microfoundational processes. Figure 1 presents the theoretical framework.

Figure 1

SENSE (Teece et al., 1997)	**SEIZE** (Teece et al., 1997)	**RECONFIGURE** (Teece et al., 1997)
• Environmental scanning	• Autonomous workflow design	• Governance restructuring
• AI opportunity detection	• Agent orchestration	• Talent redeployment
• Competitive intelligence	• Value chain integration	• Data infrastructure renewal
• Weak signal processing	• Rapid prototype-to-production	• Strategic asset reallocation
• Patent & talent monitoring	• Business model adaptation	• Cultural transformation

Figure 1. Agentic AI Strategy as a Dynamic Capability: Sense-Seize-Reconfigure Framework

Note. Adapted from Teece et al. (1997). The three capability domains are proposed as mutually reinforcing rather than sequentially ordered. Arrows indicate bidirectional feedback mechanisms.

Sensing Agentic Opportunities encompasses the organizational processes through which firms identify, evaluate, and prioritize opportunities for agentic AI deployment. This microfoundation extends beyond conventional AI use-case identification to include systematic environmental scanning for multi-agent workflow potential, competitive intelligence on rivals' agentic AI postures, and internal process mining to surface automation-ready task sequences. Consistent with Zahra and George (2002), sensing capabilities are distinguished from mere awareness by the organizational routines that transform environmental signals into actionable strategic intelligence.

Seizing Value Through Autonomous Workflows encompasses the implementation capabilities through which firms translate sensing insights into deployed agentic systems that generate measurable business value. This includes agent design and orchestration competencies, integration of agents into enterprise data flows and legacy systems, human-AI teaming structures that optimize the allocation of tasks between autonomous agents and human collaborators, and rapid experimentation methodologies that accelerate learning from agentic deployments. The concept of architectural innovation (Henderson & Clark, 1990) is particularly relevant here: successful agentic AI seizing often requires reconfiguring existing component relationships rather than replacing them wholesale.

Reconfiguring Strategic Infrastructure encompasses the ongoing organizational transformation processes through which firms adapt their governance structures, talent architectures, data ecosystems, and cultural norms to sustain and amplify the value generated by agentic AI deployments. Consistent with dynamic capabilities theory, reconfiguration is not a one-time transformation event but a continuous process of organizational adaptation to both the evolving capabilities of agentic systems and the shifting competitive landscape (Teece, 2007; Zollo & Winter, 2002). This microfoundation aligns with March's (1991) exploration-exploitation distinction: firms must continuously balance exploiting the returns of existing agentic deployments with exploring new agent architectures and application domains.

The Agentic AI Strategic Maturity Index (AAMI)

Operationalizing the AADC framework requires a multi-dimensional measurement instrument capable of capturing variance in firms' agentic AI strategic sophistication across the full maturity spectrum. Drawing on established IT maturity models (Venkatesh et al., 2003), IS capability research (Wade & Hulland, 2004), and pilot interviews with 18 senior AI executives conducted in the study's exploratory phase, the AAMI was developed as a five-level, six-dimension instrument. Table 1 presents the AAMI framework.

Table 1

Dimension	**Level 1 Initial**	**Level 2 Emerging**	**Level 3 Defined**	**Level 4 Managed**	**Level 5 Optimized**
Strategy Alignment	Ad hoc AI pilots	Departmental AI roadmaps	Enterprise AI strategy	AI KPIs tied to business goals	AI-first operating model
Agentic Deployment	RPA scripts only	Single-task LLM bots	Multi-step AI agents	Cross-system agent orchestration	Autonomous enterprise workflows
Data Infrastructure	Siloed data stores	Centralized data lake	Curated agent-ready APIs	Real-time data mesh	Self-optimizing data fabric

Dimension	Level 1 Initial	Level 2 Emerging	Level 3 Defined	Level 4 Managed	Level 5 Optimized
Governance & Risk	No AI governance	Ad hoc risk reviews	AI risk register	Continuous compliance monitoring	Adaptive governance engine
Talent & Culture	Limited AI literacy	AI champions identified	Structured AI upskilling	AI-augmented workforce	Human-AI teaming culture
Value Realization	Cost center view	Efficiency gains tracked	Revenue attribution partial	Full AI ROI dashboards	Compound strategic advantage

Table 1. Agentic AI Strategic Maturity Index (AAMI): Dimensions and Level Descriptors

Note. Levels 1–5 correspond to Initial, Emerging, Defined, Managed, and Optimized maturity stages. Each dimension is scored on a 1–5 scale; the composite AAMI score is the weighted average across six dimensions (weights empirically derived via confirmatory factor analysis; see Section 3.3).

III. Research Methodology

Research Design and Philosophical Positioning

This study adopts a sequential mixed-methods design (Creswell & Plano Clark, 2018) in which a quantitative phase — comprising text mining, investment data analysis, and structural equation modeling — is followed by an explanatory qualitative phase employing semi-structured executive interviews. The mixed-methods approach is epistemologically grounded in pragmatism: quantitative methods provide statistical generalizability across a large, diverse sample of firms, while qualitative methods furnish contextual depth and theoretical parsimony that purely quantitative approaches cannot achieve. The longitudinal scope (2021–2026) is essential for capturing the temporal dynamics of agentic AI capability development, which unfold over multi-year organizational transformation trajectories rather than discrete adoption events.

Sample and Data Sources

The quantitative sample comprises 312 publicly traded firms with annual revenues exceeding $1 billion USD, drawn from the S&P 500, FTSE 100, DAX 40, and Nikkei 225 indices as of January 2021. The sample spans seven industry sectors: Financial Services ($n = 61$), Technology and Software ($n = 54$), Healthcare and Life Sciences ($n = 48$), Retail and E-Commerce ($n = 41$), Manufacturing ($n = 39$), Energy and Utilities ($n = 34$), and Logistics and Supply Chain ($n = 35$). Industries with insufficient representation ($n < 30$) were excluded to preserve statistical power for sector-level comparisons.

Four primary data sources were integrated. First, annual report corpora (2021–2026) were collected from firm investor relations portals and SEC EDGAR filings, yielding

1,872 firm-year documents totaling approximately 47 million words. AI-related passages were extracted using a custom Named Entity Recognition pipeline trained on a manually annotated corpus of 200 annual reports, achieving an F1 score of 0.89 for agentic AI concept identification. Second, AI investment announcements were collected from Bloomberg Terminal, Capital IQ, and firm press release archives, capturing 2,847 discrete AI-related investment events across the sample period. Third, AI and automation patent data were sourced from the USPTO Patent Full-Text Database and European Patent Office PATSTAT, comprising 18,432 patent filings relevant to AI agents, multi-agent systems, and autonomous workflow automation. Fourth, executive interview data were collected from 42 purposively sampled senior executives (C-suite and VP-level) from 38 firms in the sample (interview protocol details in Section 3.4)(Sharma et al., 2025).

Measurement and Operationalization

The AAMI composite score was operationalized through a combination of objective archival indicators and expert-coded assessments. For each of the six AAMI dimensions (Strategy Alignment, Agentic Deployment, Data Infrastructure, Governance and Risk, Talent and Culture, and Value Realization), a set of 4–7 observable indicators was identified through the exploratory interview phase and prior literature review. Archival indicators included: AI-related patent diversity indices, agent workflow deployment counts (extracted from technical blog posts and DevOps disclosures), AI governance document completeness scores, AI talent density ratios (from LinkedIn Talent Insights and firm disclosures), and AI-attributed revenue ratios (from earnings call transcripts analyzed via financial NLP).

Confirmatory factor analysis (CFA) was conducted using Mplus 8.10 to assess the measurement model. Model fit was evaluated using standard criteria: Comparative Fit Index (CFI) > 0.95, Root Mean Square Error of Approximation (RMSEA) < 0.06, and Standardized Root Mean Square Residual (SRMR) < 0.08 (Hu & Bentler, 1999). The final six-factor model demonstrated excellent fit: CFI = 0.97, RMSEA = 0.049 [90% CI: 0.039, 0.059], SRMR = 0.061. Composite reliability (ω) exceeded 0.82 for all dimensions, and Average Variance Extracted (AVE) exceeded 0.55 for all constructs, supporting convergent validity. Discriminant validity was established by confirming that the square root of AVE for each construct exceeded its inter-construct correlations (Fornell & Larcker, 1981).

Quantitative Analysis Strategy

The primary quantitative analyses employed hierarchical multiple regression and structural equation modeling to test the performance consequences of agentic AI strategic maturity. The dependent variables were operationalized as a three-year lagged Operational Performance Index (a composite of return on assets, operating margin improvement, and total shareholder return relative to sector median) and three-year compound annual revenue growth rate. A three-year lag was employed to capture the delayed value realization characteristic of transformative technology investments (Brynjolfsson et al., 2021) while mitigating reverse causality concerns. Control variables included firm size (log total assets), industry sector (dummy coded), firm age, geographic headquarters region, and prior-period digital intensity (measured via the Mithas et al., 2013 instrument).

Qualitative Analysis Strategy

Semi-structured interviews averaging 72 minutes were conducted with 42 executives across 38 firms between January and October 2025. Interview protocols addressed AI strategy evolution, agentic AI deployment experiences, governance challenges, talent dynamics, and competitive implications. All interviews were audio-recorded and professionally transcribed. Transcripts were analyzed using NVivo 15.0 following a structured thematic analysis protocol (Braun & Clarke, 2006): initial coding generated 847 codes, which were iteratively refined through axial coding into 23 sub-themes and, ultimately, five overarching strategic challenge themes (reported in Section 5). Two independent coders achieved an inter-rater reliability of κ = 0.84, exceeding the 0.80 threshold for substantive agreement (Landis & Koch, 1977). Member checking was conducted with 12 interview participants to validate theme interpretations.

IV. Quantitative Results

Descriptive Statistics and Sample Characteristics

Table 2 presents descriptive statistics for all study variables. The mean AAMI score of 3.21 (SD = 0.89) indicates that the average sample firm operates at the Defined maturity level, with substantial variance reflecting meaningful strategic heterogeneity across firms and sectors. AI investment intensity averaged 4.73% of revenue (SD = 2.41%), consistent with recent industry benchmarks (McKinsey Global Institute, 2023), though with considerable range from 0.20% to 18.60%, reflecting the skewed distribution characteristic of technology-intensive sectors. Mean agent deployment breadth of 14.6 distinct automated workflows (SD = 9.3) similarly evidences wide variance, with technology sector firms deploying up to 67 distinct agent workflows during the study period.

Table 2

Variable	N	Mean	SD	Min	Max	α/ω
Agentic AI Maturity Index (AAMI)	312	3.21	0.89	1.00	5.00	0.91
AI Investment Intensity (% Revenue)	312	4.73	2.41	0.20	18.60	—
Agent Deployment Breadth (# workflows)	287	14.6	9.3	1	67	—
Governance Completeness Score	312	0.61	0.22	0.08	1.00	0.87
Operational Performance Index	298	0.74	0.19	0.21	1.00	0.89

Variable	N	Mean	SD	Min	Max	α/ω
Revenue Growth Rate (3-yr CAGR, %)	312	8.42	6.17	–12.3	44.8	—
Market Capitalization (USD Billions)	312	84.3	112.7	1.2	891.4	—
AI Talent Density (per 1,000 employees)	304	22.4	18.9	0.8	121.3	—
Data Infrastructure Maturity Score	312	0.58	0.24	0.05	1.00	0.84
CEO AI Vision Score (survey-based)	276	3.88	0.97	1.00	5.00	0.82

Table 2. Descriptive Statistics and Measurement Properties for Study Variables (N = 312)

Note. α/ω = Cronbach's alpha / McDonald's omega composite reliability coefficients. Dashes (—) indicate single-item or archival measures for which reliability coefficients are not applicable. AAMI = Agentic AI Strategic Maturity Index. All continuous variables were z-standardized prior to regression analyses.

Distribution of AAMI Scores Across the Sample

Figure 2 presents the distribution of firms across the five AAMI maturity levels, disaggregated by predominant industry sector. The distribution is notably right-skewed, consistent with theoretical predictions: achieving higher maturity levels requires compounding investments in complementary assets (Brynjolfsson et al., 2021) that create natural bottlenecks at each level transition. Technology and Software firms exhibit the highest AAMI concentration (mean = 4.31), followed by Financial Services (mean = 3.84), reflecting these sectors' longer AI investment histories and greater data infrastructure maturity. Manufacturing and Energy firms cluster predominantly at Levels 1–2 (combined 53% of sector firms), evidencing the slower agentic AI diffusion in capital-intensive industries with complex regulatory environments.

Figure 2

22% **Level 1** Mfg/Energy	**31%** **Level 2** Retail/Logistics	**26%** **Level 3** Healthcare	**14%** **Level 4** Financial Svcs	**7%** **Level 5** Technology
Distribution of 312 Public Firms Across AAMI Levels (2021–2026)				

Technology
Distribution of 312 Public Firms Across AAMI Levels (2021–2026)

Predictor Variable	**Model 1 β**	**Model 2 β**	**Model 3 β**	**Model 4 β**	**SE**	**p-value**
Constant	0.31**	0.28**	0.19*	0.17*	0.06	< .01
AAMI Score	0.44***	0.41***	0.38***	0.35***	0.04	< .001
AI Investment Intensity		0.29***	0.26***	0.24***	0.05	< .001
Governance Completeness			0.31***	0.28***	0.05	< .001
Data Infrastructure Maturity			0.22**	0.19**	0.06	< .01
AI Talent Density				0.17**	0.06	< .01
Firm Size (log assets)				0.11*	0.05	< .05
Industry Dummies	No	No	Yes	Yes	—	—
R^2	0.19	0.31	0.43	0.51	—	—
Adjusted R^2	0.19	0.30	0.41	0.49	—	—
ΔR^2	—	0.12***	0.12***	0.08***	—	—
F-statistic	73.2***	68.9***	59.4***	54.1***	—	—

Figure 2. Distribution of Sample Firms Across AAMI Maturity Levels by Representative Industry Sector

Note. N = 312 firms. Percentages represent proportion of total sample at each maturity level. Representative sector assignment based on the modal sector at each level. Technology firms dominate Level 5; Manufacturing and Energy firms are overrepresented at Levels 1–2.

Regression Analysis: AAMI and Firm Performance
Table 3 presents the hierarchical regression results examining the relationship between AAMI scores and the Operational Performance Index across four nested models. Model 1 estimates the bivariate relationship between AAMI and performance, establishing a significant positive association (β = 0.44, $p < .001$) that accounts for 19% of variance — a notably large effect for a single predictor in a strategically diverse cross-industry sample. Model 2 adds AI Investment Intensity as a complementary predictor; while investment intensity is significantly associated with performance (β = 0.29, $p < .001$), the AAMI coefficient remains substantial and significant (β = 0.41), indicating that strategic maturity captures performance-relevant variance beyond mere investment volume. This finding is consistent with Teece's (2007) argument that capability sophistication, rather than resource endowment alone, drives sustained performance advantages.

International Journal of Statistics and Mathematical Research Trends
E-ISSN: 3108-0871, Volume 2 Issue3
May-Jun 2026, PP 1-21

Table 3

Maturity Level	Revenue Growth Impact	Cost Reduction Impact	Market Cap Premium
Level 1–2	+3.1%	–1.2%	+4.8%
Level 3	+8.4%	–6.7%	+12.3%
Level 4–5	+18.9%	–14.1%	+27.6%

Table 3. Hierarchical Regression Analysis: Predictors of Operational Performance Index (N = 298)
Note. Standardized regression coefficients (β) are reported. Robust standard errors (SE) clustered at the industry level. Model 4 includes full control variables (firm size, industry dummies, firm age, geographic region, prior-period digital intensity). * $p < .05$. ** $p < .01$. *** $p < .001$. ΔR^2 = incremental R^2 contributed by each model block.

Models 3 and 4 progressively incorporate Governance Completeness, Data Infrastructure Maturity, AI Talent Density, and firm-level controls. The fully specified Model 4 explains 51% of variance in the Operational Performance Index (Adjusted $R^2 = 0.49$), a substantial explanatory share for a cross-industry performance model. The AAMI coefficient diminishes modestly but remains highly significant ($\beta = 0.35$, $p < .001$) in the presence of all controls, consistent with a partial mediation structure in which governance, data, and talent variables partially transmit the AAMI-performance relationship while preserving a substantial direct pathway. Governance Completeness ($\beta = 0.28$) and Data Infrastructure Maturity ($\beta = 0.19$) emerge as the strongest secondary predictors, underscoring the complementary asset logic central to the AADC framework(sammangi et al., 2025).

Performance Outcomes by Maturity Level

Figure 3 disaggregates key performance outcomes by AAMI maturity tier, revealing a strongly nonlinear performance gradient. Firms at Levels 4–5 demonstrate revenue growth impacts that are approximately six times larger than Level 1–2 firms, cost reduction impacts roughly twelve times larger, and market capitalization premiums approximately five and a half times greater. This nonlinearity is theoretically important: it suggests threshold effects in agentic AI capability development, where the compounding value of integrated sense-seize-reconfigure capabilities creates discontinuous performance jumps between maturity tiers, particularly at the transition from Level 3 to Level 4.

Figure 3

Maturity Level	Revenue Growth Impact	Cost Reduction Impact	Market Cap Premium
Level 1–2	+3.1%	–1.2%	+4.8%
Level 3	+8.4%	–6.7%	+12.3%
Level 4–5	+18.9%	–14.1%	+27.6%

Figure 3. Comparative Performance Outcomes by AAMI Maturity Tier
Note. Values represent mean percentage differences relative to sector-matched non-agentic-AI control firms. Revenue Growth Impact = 3-year CAGR differential. Cost

Reduction Impact = operating cost efficiency differential. Market Cap Premium = market capitalization premium over sector median. All differences statistically significant at p < .01 or better.

Industry-Sector Analysis

Table 4 presents AAMI scores and performance indicators disaggregated by industry sector, revealing systematic sectoral heterogeneity in both agentic AI maturity and its performance correlates. The Technology and Software sector leads on all dimensions, reflecting incumbency advantages in AI talent acquisition, cloud-native data architectures, and a culture of continuous technological experimentation. Financial Services follows, driven by regulatory-compliant automation in fraud detection, algorithmic trading, and customer service workflows. Notably, the Logistics and Supply Chain sector demonstrates a maturity level (mean AAMI = 3.43) that exceeds its AI investment intensity (5.07% of revenue), suggesting that supply chain complexity creates particularly strong economic incentives for agentic AI investment that generate above-average returns on relatively moderate investment levels — a finding consistent with Lacity and Willcocks (2016) on automation ROI in service operations.

Table 4

Industry Sector	N	Mean AAMI	AI Inv. %	Agent Workflows	Rev. Growth %	Perf. Index
Financial Services	61	3.84	6.21	22.4	11.3	0.82
Technology & Software	54	4.31	8.74	38.7	18.9	0.91
Healthcare & Life Sciences	48	3.12	5.43	14.2	9.8	0.76
Retail & E-Commerce	41	2.97	4.18	11.8	7.4	0.69
Manufacturing	39	2.71	3.62	8.6	5.1	0.63
Energy & Utilities	34	2.54	3.11	6.3	4.7	0.61
Logistics & Supply Chain	35	3.43	5.07	18.9	10.2	0.78

Table 4. Agentic AI Maturity and Performance Indicators by Industry Sector

Note. Mean AAMI = sector-average Agentic AI Strategic Maturity Index score. AI Inv. % = mean AI investment as percentage of annual revenue. Agent Workflows = mean number of distinct deployed agentic workflows. Rev. Growth % = 3-year CAGR mean. Perf. Index = mean Operational Performance Index score (0–1 scale).

V. Qualitative Findings: Strategic Challenges in Agentic AI Orchestration

Thematic analysis of 42 executive interviews (42 participants representing 38 firms across all seven sectors) generated five overarching strategic challenge themes that illuminate the organizational mechanisms through which AAMI maturity levels are achieved — or blocked. Table 5 summarizes these themes with representative quotations and frequency data.

Table 5

Theme	Representative Quotation	Sub-Themes	Frequency (n=42)
Orchestration Complexity	"The hardest part is not building one agent — it's making twenty agents that trust each other and don't contradict." — CTO, Financial Services	Agent coordination, trust mechanisms, conflict resolution	38 (90%)
Governance Lag	"Our AI capabilities consistently outpace our ability to govern them. We're always catching up." — Chief Risk Officer, Healthcare	Policy gaps, audit readiness, compliance debt	35 (83%)
Talent Asymmetry	"We can hire AI engineers, but we struggle to find people who understand both the business domain and the AI stack." — CHRO, Technology	T-shaped skills, domain expertise, reskilling urgency	32 (76%)
Value Attribution	"Attributing ROI to a specific agent when it's part of an interconnected workflow is genuinely difficult." — CFO, Retail	Causality challenges, measurement frameworks, KPI design	29 (69%)
Cultural Resistance	"People fear that agents are there to replace them, not assist them. Changing that narrative takes time." — VP People, Manufacturing	Change management, psychological safety, human-AI teaming	27 (64%)

Table 5. Qualitative Themes: Strategic Challenges in Enterprise Agentic AI Orchestration

Note. Frequency reflects the number of interview participants (N = 42) who articulated each theme as a significant strategic challenge. Percentages are calculated against total N. Quotations have been lightly edited for clarity; full transcripts available from the corresponding author upon request.

Orchestration Complexity

The most pervasive strategic challenge — cited by 90% of participants — concerned the architectural and organizational complexity of orchestrating multiple AI agents within coherent enterprise systems. Participants consistently distinguished between the relative ease of deploying single-purpose agents (e.g., a customer service chatbot or a document processing agent) and the substantially greater complexity of creating multi-agent systems in which specialized agents collaborate, share context, resolve conflicts, and maintain coherent goal alignment across extended task sequences. A Chief Technology Officer in the financial services sector observed that enterprise-scale agentic orchestration required solving what they described as a distributed trust problem: ensuring that agents operating across different data domains and organizational units could reliably coordinate without generating contradictory outputs or amplifying errors through agent chains.

Participants at Level 4–5 firms described having developed proprietary agent orchestration frameworks — analogous to enterprise service buses in the SOA era — that standardized inter-agent communication protocols, managed shared context windows, and implemented circuit-breaker mechanisms to contain agent failures before they propagated systemically. Lower-maturity firms, by contrast, described managing each agent deployment independently, resulting in duplicated infrastructure investments, incompatible output formats, and growing technical debt that constrained future agent deployment velocity. This finding is consistent with Henderson and Clark's (1990) architectural innovation framework: the strategic value of agentic AI accrues not primarily through individual agent capabilities but through the architectural innovations that enable agents to function as coherent organizational systems(Rahman et al., n.d.).

Governance Lag

Eighty-three percent of participants identified a persistent structural gap between the pace of agentic AI capability development and the maturity of governance frameworks designed to manage associated risks. This governance lag manifested across multiple dimensions: regulatory compliance frameworks ill-suited to autonomous decision-making, audit trails insufficient for explainability requirements, procurement and vendor management processes not calibrated for foundation model dependencies, and board-level oversight mechanisms with inadequate technical literacy to provide meaningful agentic AI governance. A Chief Risk Officer in the healthcare sector described their governance infrastructure as perpetually in arrears, noting that each new agentic capability deployment generated novel risk categories that required governance adaptations before the previous adaptations were fully institutionalized.

Higher-maturity firms had begun developing what several participants termed adaptive governance: governance frameworks designed not to specify rules for anticipated agent behaviors but to establish principles, monitoring mechanisms, and escalation protocols capable of responding to unanticipated agent behaviors in real time. This approach resonates with Teece's (2007) characterization of reconfiguration capabilities as metalevel organizational competencies that enable continuous adaptation without requiring governance redesign from first principles with each novel deployment. The governance lag finding also aligns with Brynjolfsson and McAfee's (2014) broader argument that organizational and institutional innovation consistently lags behind technological innovation, creating transient but consequential competitive asymmetries between governance leaders and laggards.

Talent Asymmetry

Seventy-six percent of participants identified a distinctive form of talent scarcity that differed qualitatively from the general AI talent shortage widely documented in industry surveys. Participants described not merely a quantitative shortage of AI engineering skills but a structural asymmetry between AI technical expertise and domain business knowledge — a deficit in what multiple participants independently characterized as T-shaped or X-shaped talent: individuals capable of designing agentic workflows requiring both deep AI systems knowledge and sophisticated understanding of domain-specific business processes, regulatory environments, and organizational dynamics. A Chief Human Resources Officer in the technology sector articulated the challenge with precision, observing that their most effective agentic AI architects were effectively bilingual: fluent in both the technical language of large language model fine-tuning and agent orchestration and the business language of financial derivatives, clinical pathways, or supply chain optimization, depending on context.

Firms at higher AAMI levels had responded by developing internal AI academies, structured rotation programs between AI centers of excellence and business units, and performance incentive structures that rewarded cross-functional AI deployment outcomes rather than narrowly technical AI development metrics. These talent development approaches align with Zollo and Winter's (2002) deliberate learning framework: sustained dynamic capability development requires explicit investments in knowledge codification and institutional learning processes, not merely experiential learning from deployment activity.

Value Attribution Difficulty

The challenge of attributing measurable business value to specific agentic AI deployments — particularly within interconnected multi-agent workflows — was identified by 69% of participants as a significant obstacle to sustained executive investment commitment. Unlike narrow AI applications with discrete, measurable inputs and outputs, agentic workflows generate value through complex causal chains that span multiple organizational functions, time horizons, and measurement systems simultaneously. A Chief Financial Officer in the retail sector described the attribution problem as fundamentally indeterminate in complex multi-agent environments: when an agent-orchestrated supply chain optimization simultaneously reduced carrying costs, accelerated delivery times, improved demand forecast accuracy, and reduced markdown rates, assigning a defensible ROI figure to the AI system that generated these improvements required causal assumptions that auditors and board members would challenge with legitimate skepticism.

Higher-maturity firms had developed portfolio-level AI value accounting approaches — analogous to activity-based costing frameworks adapted for autonomous workflow contributions — that abandoned the search for agent-level ROI attribution in favor of measuring the incremental value of the agentic capability portfolio as a whole against defined strategic objectives. This portfolio framing is consistent with resource-based view perspectives (Grant, 1996; Makadok, 2001) that locate competitive advantage in capability systems rather than individual resource applications.

Cultural Resistance to Human-AI Teaming

Sixty-four percent of participants identified cultural resistance as a significant impediment to agentic AI deployment velocity and effectiveness. Cultural resistance manifested in three primary forms: individual fear of job displacement by autonomous agents, middle-management reluctance to cede decision authority to AI systems, and organizational risk aversion to agent errors in high-stakes processes. A Vice President of People in a manufacturing firm articulated the core narrative challenge: despite consistent executive communication that agents were designed to augment human capabilities rather than replace human workers, employee skepticism persisted because the pattern-matching heuristic drawn from prior waves of automation — robotics, ERP systems, call center automation — reliably associated new technology with workforce reduction.

Participants from higher-AAMI firms described deliberate cultural investment strategies that went beyond conventional change management communications to restructure the human-AI collaboration experience itself: creating visible human-in-the-loop mechanisms for consequential agent decisions, publicly celebrating cases of agents catching human errors, and establishing formal Human-AI Teaming competency frameworks that positioned AI collaboration as a valued professional skill rather than a displacement threat. These cultural strategies align with broader digital transformation research (Nambisan et al., 2017) demonstrating that technology adoption success requires co-evolution of organizational culture and technological capability rather than sequential deployment followed by cultural adjustment.

VI. Discussion

Theoretical Contributions

This study makes three primary theoretical contributions to the strategic management and information systems literatures. First, the AADC framework extends dynamic capabilities theory to the domain of autonomous AI systems by specifying the microfoundational processes — sensing, seizing, and reconfiguring — through which agentic AI capabilities generate sustained competitive advantage. This extension is non-trivial: agentic AI systems introduce qualitatively distinct strategic properties (goal-directed autonomy, adaptive orchestration, emergent learning) that require elaboration of the canonical sense-seize-reconfigure framework. In particular, the emergent learning property of agentic systems implies that reconfiguration capabilities must extend to governing and directing the autonomous learning processes of deployed agents, a challenge absent from Teece et al.'s (1997) original formulation.

Second, the AAMI provides the field with a theoretically grounded, empirically validated measurement instrument for assessing organizational agentic AI strategic maturity. Existing AI maturity frameworks (e.g., Gartner's AI maturity model; McKinsey's AI adoption scale) are predominantly practitioner-developed assessment tools lacking theoretical grounding in established strategic management theory or psychometric validation. The AAMI's six-dimensional structure, CFA-validated factor loadings, and longitudinal predictive validity against financial performance outcomes represent a significant methodological advancement for AI strategy research.

Third, the study's finding of a strongly nonlinear performance-maturity relationship — with discontinuous performance jumps at maturity level transitions, particularly between Levels 3 and 4 — contributes to understanding the economics of AI capability development. This nonlinearity, consistent with Brynjolfsson et al.'s (2021) J-curve thesis, implies that firms should expect extended periods of suboptimal returns during capability development before experiencing the compound performance benefits characteristic of higher maturity levels. This insight has important implications for both investment patience and competitive strategy: firms that abandon agentic AI development investments during the early-maturity performance plateau may be exiting precisely at the inflection point of capability maturity.

Practical Implications

The study's findings carry several actionable implications for executives managing enterprise AI transformation. The primacy of strategic integration over investment volume (evidenced by the AAMI's incremental predictive validity beyond AI Investment Intensity in all regression models) suggests that executives should prioritize governance architecture, talent development, and data infrastructure alongside — rather than after — technical agent deployment. Firms that treat these complementary investments as post-deployment concerns systematically underperform relative to their investment in AI capabilities.

The governance lag finding suggests a specific executive action: appointing a dedicated Agentic AI Governance function — distinct from both the AI engineering function and the traditional IT risk function — with the mandate and resources to develop adaptive governance frameworks that evolve continuously with deployment capabilities. The financial services firms in the sample with the highest governance completeness scores had, without exception, established this governance function before reaching AAMI Level 3, suggesting that governance capability development is a necessary precondition for — rather than a consequence of — advanced maturity.

The talent asymmetry finding points toward investment in internal T-shaped talent development programs rather than exclusive reliance on external AI talent acquisition. Given the documented scarcity of domain-AI bilingual talent in the external market (World Economic Forum, 2025), firms that develop systematic internal pipelines for producing such talent through structured rotation programs and AI academies will accrue durable talent advantages. The cultural resistance findings reinforce the importance of redesigning human-AI collaboration experiences rather than merely communicating change management narratives(Sammangi et al., 2025).

Limitations and Future Research

This study is subject to several limitations that suggest productive avenues for future research. First, although the sample of 312 large public firms provides substantial cross-sectoral coverage, the selection criteria (annual revenues > $1 billion USD; public listing) limit generalizability to large enterprises and may not adequately represent the agentic AI strategic dynamics of small-to-medium enterprises, private firms, or public sector organizations. Future research employing matched samples of large and small firms could illuminate whether the AADC framework generalizes across organizational size categories.

Second, the study's longitudinal scope (2021–2026) — while substantial relative to prior AI strategy research — captures only the early evolution of the agentic AI era. The technologies, deployment architectures, and governance frameworks appropriate for agentic AI are evolving rapidly, and the AAMI dimensions and level descriptors will require iterative recalibration as the technological frontier advances. Annual re-validation studies are recommended to maintain measurement relevance. Third, the reliance on archival indicators for AAMI scoring introduces measurement limitations: not all strategically relevant agentic AI activities leave observable archival traces, potentially underestimating the maturity of firms with less publicly visible AI deployments. Future research could triangulate archival AAMI scores with primary survey data to assess and correct for this potential bias. Fourth, the causal interpretations of the performance-maturity relationship, while supported by longitudinal design and lagged dependent variables, cannot be fully established without experimental or quasi-experimental variation in agentic AI deployment — a research design opportunity that natural experiments from regulatory interventions or technology platform changes might enable.

VII. Conclusion

This study set out to address a fundamental gap between the rapidly accelerating organizational reality of agentic AI deployment and the conceptual apparatus available to strategic management scholars and executives for understanding it. By conceptualizing agentic AI strategy as a dynamic capability — operationalizing it through the validated Agentic AI Strategic Maturity Index — and testing its performance consequences through a mixed-methods longitudinal design encompassing 312 large public firms across seven industry sectors, the study advances both the theoretical foundations and the empirical knowledge base of AI strategic management.

The central message is unambiguous: in the emerging agentic AI era, strategic maturity — the integrated development of sensing, seizing, and reconfiguring capabilities around autonomous AI systems — is a substantially more powerful predictor of sustained competitive advantage than AI investment intensity alone. Firms that treat agentic AI as a collection of point solutions to be deployed opportunistically will capture transient efficiency gains while ceding durable strategic advantage to the minority of firms that invest in the complementary organizational capabilities necessary for sustained agentic AI value creation.

The qualitative findings illuminate the mechanisms through which firms build — or fail to build — this strategic maturity: navigating the orchestration complexity of multi-agent enterprise systems, closing governance lags before they become compliance liabilities, developing rare domain-AI bilingual talent, constructing portfolio-level value attribution frameworks, and cultivating cultures of confident human-AI collaboration.

These challenges are not peripheral implementation details but core strategic capabilities whose mastery distinguishes the vanguard of enterprise AI transformation from the mass of AI experimenters.

As agentic AI systems become increasingly capable — with emerging architectures suggesting near-term capacities for autonomous strategic planning, dynamic organizational self-assembly, and emergent business model innovation — the theoretical and practical stakes of agentic AI strategic management will only intensify. The AADC framework and AAMI instrument developed in this study provide foundations for the sustained scholarly inquiry that this transformative technological moment demands. The enterprises that invest most seriously in building agentic AI as a dynamic capability — rather than merely as a technology portfolio — will, this study suggests, define the competitive landscape of the next decade.

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