The Development of Humanities and Social Sciences, 2025, 1(5), 133-157
https://doi.org/10.71204/qeqqvj92

The Impact of Artificial Intelligence on Strategic Technology Management: A Mixed-Methods Analysis of Resources, Capabilities, and Human-AI Collaboration

Massimo Fascinari [1,*], Vincent English [1]

[1] Telematic University UNINETTUNO (TUU), Rome, Italy

[*]**Corresponding Author**
Massimo Fascinari

m.fascinari@students.uninettunouniversity.net

Received: 19 December 2025 / Accepted: 3 January 2026 / Published online: 4 January 2026

Abstract

This paper investigates the effective integration of artificial intelligence (AI) into Strategic Technology Management (STM) practices to enhance the strategic alignment and effectiveness of technology investments. The study aims to understand how AI fundamentally transforms STM under conditions of uncertainty and what organizational prerequisites are necessary for successful adoption. A mixed-methods approach was employed, combining quantitative analysis of survey data (n=230) with qualitative insights derived from expert interviews (n=14). This methodology addressed three critical research questions: the success factors AI introduces for STM roadmap formulation, the resources and capabilities required for AI-enhanced STM, and the optimal design principles for human-AI interaction in complex STM tasks. The findings demonstrate that AI transforms STM by enabling data-driven strategic alignment and continuous adaptation, with success depending upon cultivating proprietary data ecosystems, specialized human talent, and robust governance capabilities. The research synthesizes these elements into the AI-based Strategic Technology Management (AIbSTM) conceptual framework, structured across strategic alignment, resource-based view, and human-AI interaction layers. The research concludes that the most viable integration trajectory is human-centric augmentation, where AI serves as a collaborative partner to human judgment rather than an autonomous replacement. This work extends the Resource-Based View to AI contexts and offers a prescriptive framework for practitioners navigating AI integration in strategic technology management.

Keywords: Strategic Technology Management; Artificial Intelligence; Human-AI Collaboration; Resource-Based View; Technology Roadmapping

1. Introduction

The persistent challenge of underperforming technology investments poses a substantial problem for contemporary organizations. Research by Gartner reveals that less than half of organizations achieve expected value from their Information Technology investments, (Stegman, Guevara et al., 2023) an issue amplified by the increasing budgets allocated to technological initiatives. This failure rate in technology investments derives primarily from suboptimal Strategic Technology Management (STM) practices, particularly the misalignment between business objectives and technology strategies.

Strategic Technology Management - the process of aligning an organization's technology with its corporate-level business strategies to create and sustain competitive advantage (Sahlman and Haapasalo, 2012) - has become increasingly complex in the digital age. The rapid integration of artificial intelligence across various domains presents both an unprecedented opportunity and a fundamental challenge for organizations seeking to enhance their STM structures and practices. As AI technologies mature from experimental applications to core business capabilities, organizations face a transformation for which many are inadequately prepared.

This research addresses a critical gap in literature: despite extensive work on AI's technical aspects and broader strategic applications, there exists no unified, integrated framework for its systematic embedment within STM practices. This deficit highlights a fundamental challenge - how to transition from conceptual understanding of AI's capabilities to pragmatic and strategic implementation within existing operational frameworks. The significance of this research comes from recognizing AI not merely as another technological tool, but as a catalyst requiring a fundamental shift in how organizations approach strategic technology management.

The research is motivated by a central paradox: while AI promises to address human attention scarcity and enhance decision-making capabilities, it simultaneously creates new demands for human oversight, particularly in verifying outputs for complex strategic tasks. This tension is further complicated by divergent perspectives on AI's ultimate role. One perspective positions AI as augmenting human capabilities, enabling strategists to focus on higher-value activities like ethical oversight and creative problem-solving. Conversely, a more transformative vision explores pathways toward greater automation through AI agents, exemplified by concepts like the "Agentic CTO".

The primary aim of this study is to identify how organizations can leverage AI to enhance the value of their technology investments by analysing what barriers AI can reduce to improve managerial productivity and their ability to implement successful strategic technology management roadmaps. This investigation addresses three interconnected research questions:

RQ1: What critical success factors does AI innovate for formulating the STM roadmap under conditions of creativity and uncertainty?

RQ2: What resources and capabilities should organizations have to enhance their STM roadmap formulation in complex scenarios with AI?

RQ3: How should the interaction between humans and AI be designed to enhance the performance of complex STM tasks?

Through a comprehensive mixed-methods approach combining literature review, quantitative survey data, and qualitative expert interviews, this research develops the AI-based Strategic

Technology Management (AIbSTM) conceptual framework. The framework serves as both a theoretical contribution and practical guide, synthesizing the technical capabilities of AI with the essential human and organizational aspects of STM.

The paper is structured as follows: Section 2 reviews relevant literature across three core themes - STM success factors, the Resource-Based View applied to AI, and human-machine interaction dynamics. Section 3 outlines the mixed-methods methodology. Section 4 presents findings from both quantitative and qualitative phases. Section 5 discusses these findings in relation to the research questions. Finally, Sections 6 concludes with theoretical and practical implications of AI in strategic technology management.

2. Literature Review

2.1. Strategic Technology Management and Success Factors

Strategic Technology Management involves planning, organizing, leading, and controlling technology implementations to support organizational business strategy (National Research Council, 1987; Roberts, 2001). It contributes to formulating and executing long-term goals by allocating necessary strategic technology resources (Sahlman, 2010; Deutsch and Berényi, 2023).

The literature identifies several critical success factors for effective STM. Strategic technology decisions prove most effective when aligned with business and competitive strategies, ensuring technology choices provide significant cost advantages or create highly valued stakeholder capabilities (Sahlman and Haapasalo, 2012). Success is influenced by broader organizational factors including industry context, inter-organizational strategies, cross-functional collaboration, and human resource management practices (Meer and Calori, 1989). Additionally, competitive environment, management control style, and incentive systems play significant roles in guiding strategic choices (Sands, 1991).

Effective leadership and supportive organizational culture emerge as integral success factors. Leaders guide problem definition and solution development while establishing change-receptive cultures. However, research often overlooks how leader behaviours, collaboration, and processes directly influence organizational technology innovation (Kurzhals et al., 2020). Cooper (2024) advocates for a "four-point dialectic" that evenly distributes attention among strategist, technology, customer, and industry trends. Successful technology adoption requires integrating new technologies with existing culture (Borkovich et al., 2015) and accumulating knowledge through experience and "learning by doing" to enhance technological capabilities over time (Kharbanda, 2001).

As organizations navigate cultural integration and learning challenges, particularly in volatile, uncertain, complex, and ambiguous (VUCA) environments, the proliferation of large language models and evolution of AI-based agents increasingly create opportunities for achieving strategic alignment (Krishnan, 2025) through their ability to simulate scenarios and analyse vast datasets (Holmström and Carroll, 2024, Alexander, 2025). AI transforms alignment by linking organizational goals and technology roadmaps through data, enhancing adaptability through scenario simulation. Its predictive capabilities improve decision-making, enabling organizational ambidexterity - exploring new opportunities while exploiting existing strengths (Daskalopoulos and Machek, 2025).

A core AI benefit is accelerating insight generation from extensive datasets, enabling bold, evidence-based strategies moving beyond intuition (Biloslavo et al. 2024). Real-time data analysis and predictive foresight maintain alignment in rapidly changing environments (Schrage et al., 2024). AI addresses operational challenges like "blank page syndrome" by generating creative starting points and structuring unstructured data, preserving human judgment while enhancing dynamic decision-making capabilities (Yun et al., 2025).

2.2. Resource-Based View and AI Capabilities

The Resource-Based View (RBV) postulates that firms achieve sustained competitive advantage through possessing and deploying resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Wernerfelt, 1984; Barney, 2001). This framework proves particularly relevant for analysing AI adoption, as its uneven implementation across firms can be explained by differences in their access to AI-related VRIN resources and capabilities.

Resources encompass tangible or intangible assets firms own or control, while capabilities represent the ability to effectively combine, deploy, and leverage these resources strategically. AI requires specific resources including powerful computational hardware, natural language processing capabilities (Krishnan et al., 2019), and large datasets for effective decision-making (Jones and Wray, 2006, Massoudi et al., 2024). However, resources alone prove insufficient. Organizations must develop capabilities enabling collaboration with AI researchers through open innovation while retaining distinct internal execution strategies (Haefner et al., 2021; Agarwal, 2025).

The scaling law of AI performance critically influences resource requirements, demonstrating that improvements depend on jointly expanding data, compute, and model size (Kaplan et al, 2020). This creates resource asymmetries predicted by RBV to underpin competitive advantage. However, when AI capabilities are commoditized as services, smaller firms can compete by leveraging unique data niches, domain expertise, or inimitable governance routines (Alexander , 2025; Diyin and Bhaumik, 2025).

Governance capabilities emerge as particularly critical, encompassing data-driven workflow management, role definition, human-AI collaboration fostering, and strategic AI positioning (Perifanis and Kitsios, 2023). Effective governance necessitates data ownership, curation capabilities, ethical frameworks, risk assessments, and lifecycle compliance automation (Floridi et al., 2025; IBM, 2025). It is worth noting that legislation and regulations such as the EU AI Act may transition governance from a differentiating capability to a market prerequisite.

Human talent represents another differentiating resource, valuable for specialized, often tacit knowledge. Integrating AI with strategic management demands "fusion skills" combining domain expertise with AI literacy (Purdy and Williams, 2023; Mäkelä and Stephany, 2024) and requiring middle management to acquire AI skills for bridging the communication between AI adopters and inhibitors (Rowe et al., 2024). Organizations necessitate integrated approaches including targeted hiring, reskilling, and workforce reconfiguration to position AI talent as an effective differentiator.

Organizational culture proves foundational for success. A data-centric culture establishes robust governance for quality and privacy while promoting data-driven decision-making. Agile cultures respond effectively to AI-driven changes, developing digital competencies and enabling operative AI tool usage (Čižo et a., 2025; Li, 2025). Cultural readiness requires proactive change management and AI literacy programs securing stakeholder buy-in (Abdullah et al., 2025).

However, cultural readiness alone proves insufficient given AI's unprecedented pace of innovation. With AI technology rapidly evolving, organizations require dynamic capabilities - organizational processes enabling environmental adaptation (Teece et al.m 1997) - prove essential for sustained AI advantage. These include sensing opportunities, seizing resources for promising initiatives, and transforming workflows and structures (Owusu and Agbesim 2025). Self-improvement capabilities represent an advanced frontier, with techniques like automated quality control loops and AI-enabled R&D allowing dynamic strategy adjustments (Lu et al., 2024, Kokotajlo et al., 2025).

2.3. Human-AI Interaction in Strategic Contexts

Integrating AI into organizational decision-making introduces significant complexities requiring well-thought-out strategies (Davenport, 2021; Kesting, 2024) with boundary between successful AI integration and non-successful AI integration scenarios forming a "jagged technological frontier" where optimal approaches remain incompletely understood (Dell'Acqua et al., 2023). AI adoption depends fundamentally on human-AI relationships, requiring an understanding of motivations, emotions, behaviours, and attitudes (Chernov et al., 2020, Haefner et al., 2021), with technology leaders playing a crucial role in guiding organizations through the transformation toward cognitive economies where intelligent machines become central to the workforce (Naqvi, 2017; Schrage et al., 2024).

Culturally, organizations should address leadership resistance by demonstrating AI value through executive training that enables collaborative data interrogation and scenario exploration. Human-AI integration models designed to deliver tangible benefits should include safeguards to prevent task polarization, whereby simple tasks become simpler while complex tasks grow more complex (Simkute et al., 2024), creating a paradox in which high human attention is required for verifying AI outputs despite AI being intentionally engaged to address human attention scarcity (Eriksson et al., 2020; Woodruff et al., 2024).

In the literature, augmentative patterns where AI supports iterative refinement and knowledge acquisition emerge as predominant. Regarding complex tasks, avoiding paradoxes necessitates designing co-creation cycles, explanatory dialogues, and verification mechanisms that position AI as a collaborative companion (Accenture, 2025; Handa et al., 2025). 'Copiloting' exemplifies this complexity, structuring work around natural language interactions and benefitting from AI's content creation capacity (Banh et al., 2025).

Trust emerges as a cornerstone of collaboration with the "black box" nature of sophisticated AI models eroding confidence (Floridi, 2023). While Explainable AI addresses aspects of this opacity through human-centred explanations and has proven successful in high-stakes fields (Bila et al., 2025), building trust extends beyond explainability to encompass privacy, bias, and control concerns. Trustworthy AI frameworks emphasize human oversight, demonstrated competence, and uncertainty reduction (Li et al., 2024), built on techniques such as multi-stage reasoning and Introspective Uncertainty Quantification that enable AI self-critique and provide consistent uncertainty estimates (Mei et al., 2025).

Despite these advances, significant risks persist in adopting a 'Copiloting' model. These range from AI facilitating labour exploitation through "growth without calories" - where firms expand without hiring (Galloway, 2024) - to over-reliance risks that lead to cognitive degradation, undermining motivation and critical thinking. In response, recent research (Singh et al., 2025; Wu et al., 2025) suggests reframing the human role as "steward," one who actively verifies outputs and refines prompts (Collins et al., 2025; Lee et al., 2025), representing a more effective and valuable human-AI collaborative model.

3. Methodology

3.1. Research Philosophy and Design

This study employed a pragmatic mixed-methods design to investigate AI's impact on Strategic Technology Management. The methodology was grounded in critical realist ontology, which recognizes that reality exists independently of our perception, while also acknowledging that human understanding shapes how we know that reality (Saunders and Lewis, 2017). This philosophical approach allowed the exploration of both objective organizational structures and subjective individual experiences within those structures.

The adopted mixed-methods approach is a sequential explanatory one, beginning with quantitative data collection to establish broad foundations, followed by qualitative inquiry providing contextual depth (Creswell, 2021). This structure ensured initial quantitative findings informed and directed subsequent qualitative investigation, yielding richer, more nuanced understanding. The strength of the adopted mixed-methods approach lay in its ability to provide explanations that neither method could achieve alone.

3.2. Quantitative Phase: Online Survey

The first quantitative phase used an online survey through Google Forms between November 2024 and February 2025. The survey was designed to test findings and address gaps from existing literature while measuring the prevalence of AI adoption among the broader professional population.

3.2.1. Survey Design

The survey comprised 21 sections containing 120 single-choice questions, predominantly utilizing 5-point Likert scales. Sections addressed themes including AI adoption in STM practices, trust levels, cultural readiness, human-AI interaction, resources, skills, and investment priorities. Questions were structured to operationalize abstract constructs such as perceived workload associated with AI output verification, trust in AI systems, and organizational AI governance preparedness. The instrument underwent pilot testing to ensure question neutrality and minimize response bias.

3.2.2. Sampling and Data Collection

The study employed convenience and snowball sampling through professional networks. Initial distribution to LinkedIn Groups reached potential audience of 7 million accounts, yielding limited responses. Subsequently, distribution to the researcher's personal LinkedIn network (1,726 users) proved more effective, generating 278 responses with 230 valid completions (82.7% validity rate).

3.2.3. Statistical Analysis

Quantitative data underwent rigorous statistical analysis including:

- Reliability testing using Cronbach's Alpha ($\alpha = 0.906$ for 53 items), demonstrating high internal consistency
- Descriptive statistics calculating means and standard deviations for Likert-scale items
- Pearson correlation analysis investigating relationships between variables
- Linear regression analysis examining predictive relationships.

Statistical analysis revealed significant relationships, including positive correlation between AI's strategic action definition role and uncertainty handling ability ($r=0.52$, $p<0.01$), and predictive relationship between perceived AI effectiveness and future adoption intentions ($\beta=0.63$, $p<0.001$).

3.3. Qualitative Phase: Expert Interviews

Following quantitative analysis, the study transitioned to qualitative inquiry using semi-structured interviews with 14 industry experts. This phase employed purposive sampling to select participants who could provide rich, contextual insights based on their specific expertise.

Four distinct professional groups were targeted with the aim of obtaining a broad perspective on strategic technology management decision-making: (1) those responsible for making strategic technology decisions (Chief Technology Officers/Chief Information Officers/IT Directors); (2) those providing AI tools (Strategic Portfolio Management Product/Service Vendors); (3) those designing AI architectures (AI Platform Architects); and (4) those developing conceptual models to support such decisions (Academic Researchers).

Response rates varied across groups, with approximately 10% of all professionals contacted participating in the interviews - a rate reflecting expected executive-level engagement patterns - providing sufficient data for rich qualitative analysis.

3.4. Interview Protocol

The semi-structured interview guide drew on survey findings to explore emerging themes in greater depth. The protocol addressed six key themes:

- AI adoption and readiness in strategic management
- Critical resources for AI integration in technology strategy decision-making

- Speculative views on autonomous and automated AI in STM (the "Agentic CTO" concept)
- Balance between human expertise and AI capabilities
- Strategic roadmap formulation under VUCA conditions
- Trust, accountability, and ethical concerns

Interviews were conducted remotely via Microsoft Teams between April and June 2025, with sessions digitally recorded and transcribed using automated services. The semi-structured format allowed flexibility to explore emergent topics while maintaining consistency across core themes.

3.5. Data Analysis and Integration

3.5.1 Qualitative Analysis

Interview transcripts underwent systematic analysis using NVivo software. Initial open coding generated 651 distinct codes, which were subsequently clustered according to the research questions and further refined into 20 categories directly linked to those questions.

3.5.2 Data Triangulation

Integration of quantitative and qualitative data occurred at the interpretation stage. The mixed-methods design enabled meta-inferences (Tashakkori and Teddlie, 2010) greater than individual parts' sum. Quantitative findings provided broad landscape understanding, while qualitative data offered contextual depth necessary for interpretation. For example, survey results showing low AI adoption for strategic functions were explained through interviews revealing organizational barriers and cultural resistance.

This triangulation enhanced validity and reliability by ensuring patterns observed in one dataset could be validated or contextualized by another. The convergence of findings from diverse sources provided robust, well-substantiated conclusions about AI's impact on STM.

4. Findings and Analysis

The empirical findings of the research are presented by combining both the quantitative survey results and the qualitative insights generated from expert interviews. The purpose of this structure is to align with the sequential explanatory design of the study: the survey establishes broad patterns and relationships in organisational practice, while the interviews provide depth, context, and interpretation. Together, these complementary phases create a robust evidence base on which meta-inferences can be drawn.

Figure 1 and Table 1 below provide information about participants' demographics, including professional roles, industries, and geographic distribution, for the quantitative survey respondents and semi-structured interview participants, respectively.

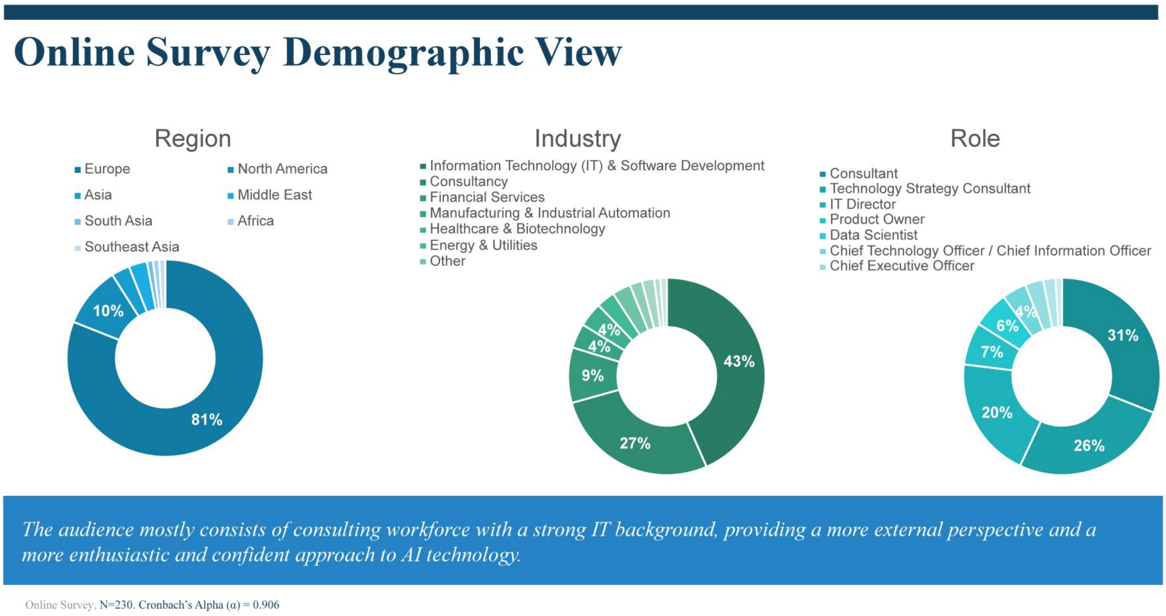

Figure 1. Overview of the Online Survey respondents' demographics

Table 1. Semi-structured expert interviewees list

Interview #	Geography	Job Role / Position	Years of Experience
Interview 1	North America	Finance CIO, Managing Director, Global IT at a leading Consulting Firm	>20
Interview 2	South America	Professor of Technology and Innovation Management	>15
Interview 3	North America	AI for IT CIO, Senior Manager at a leading Consulting Firm	>25
Interview 4	South Asia	Strategy and Business Operations Lead	>15
Interview 5	Europe	IT Strategy and Execution Lead	>40
Interview 6	Europe	CTO, Chairman and Board Member	>35
Interview 7	North America	CISO and Adjunct Professor	>30
Interview 8	North America	CTO and Head of Software Development	>35
Interview 9	North America	CTO and co-funder	>25
Interview 10	North America	CTO and Product Engineering Lead	>15
Interview 11	North America	GenAI Consultant	>10

Interview 12	North America	Founder, AI Governance and CTO	>20
Interview 13	Middle East	Technology Executive at a leading SPM and EA platform vendor	>25
Interview 14	Southeast Asia	Futurist and Board Advisor	>40

4.1. Strategic Alignment and the AI factor

4.1.1. Survey Findings on AI's Role in STM

The quantitative analysis (visualized in Figure 2) revealed AI's moderate yet evolving impact on strategic technology roadmap formulation. AI demonstrated strongest value in providing leadership advisory functions (M=3.24, SD=0.99), suggesting effectiveness in integrating data-driven insights into strategic formulation. However, AI's capability to navigate VUCA scenarios remained limited (M=3.08, SD=1.04), indicating current inability to fully manage unpredictability inherent in uncertain environments. AI proved most effective in tactical roadmap aspects, particularly defining "Know WHAT" (M=3.47, SD=1.00) and "Know HOW" (M=3.54, SD=1.00). Conversely, effectiveness diminished for higher-level strategic elements as strategic intent "Know WHY" (M=3.14, SD=1.00) and timing "Know WHEN" (M=3.00, SD=1.00).

Limited data availability and quality (M=4.06, SD=1.00) directly impact the reliability of AI in providing recommendations under uncertainty. This relationship is evidenced by a strong positive correlation between AI's role in strategic action definition and its uncertainty handling ability ($r=0.52$, $p<0.01$), with the highest correlation observed for the "Know WHY" dimension ($r=0.49$, $p<0.01$).

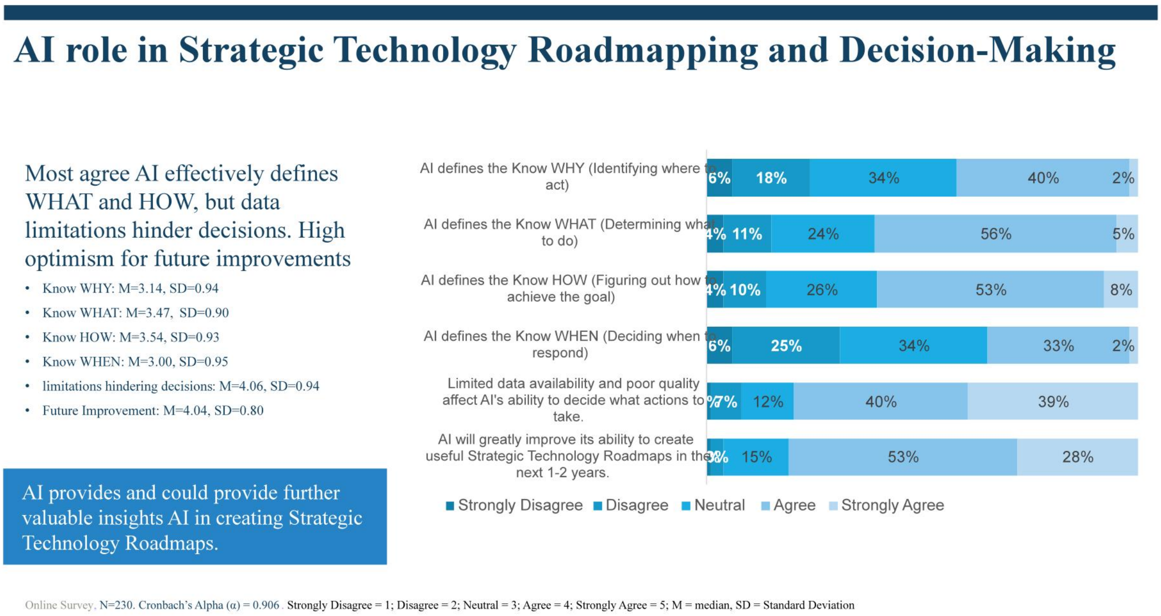

Figure 2. AI role in Strategic Technology Roadmapping and Decision-Making

Organizational challenges significantly impeded AI adoption, particularly weak leadership mandates (M=2.75, SD=1.00) and organizational resistance to change (M=3.48, SD=1.00). Nevertheless, despite these current limitations, respondents remained optimistic about AI's potential for VUCA management, anticipating substantial improvements within 1-2 years (M=3.84, SD=0.85).

4.1.2. Expert Perspectives on Strategic Alignment

Interview analysis revealed that AI's role extends beyond operational optimization to enable enhanced strategic clarity. Experts consistently emphasized the necessity of defining clear business objectives prior to any AI deployment. As one CTO articulated: "Creating what I call a business architectural definition of what it is that I'm trying to achieve" is fundamental to successful alignment regardless of AI. Seeking strategic clarity should influence how organizations evaluate their AI investments. Rather than relying solely on traditional ROI metrics, respondents indicated a need to assess AI initiatives based on their capacity to enable outcomes that were previously unattainable. As one expert explained, AI enables companies to "achieve goals that were not achievable before," representing a "huge opportunity." However, respondents emphasized that realizing these goals requires rigorous alignment between investments and well-defined business capabilities, cautioning against fragmented initiatives that pursue "silver bullet" solutions without sufficient organizational maturity.

Interviews revealed AI's profound limitations in authentic strategic cognition. Multiple experts warned of AI's inability to capture subjective strategic elements - the "air" in strategic workshops encompassing unspoken nuances, cultural DNA, and accumulated leadership intuition. One interviewee cautioned that AI-generated strategies risk being "inauthentic and disingenuous," technically correct but lacking embedded human context vital for true alignment.

The "Agentic CTO" concept, inspired by NVIDIA CEO Jensen Huang's vision of AI agents replacing human technology leadership (NVIDIA, 2025), was largely rejected by interviewees. One expert suggested this narrative primarily serves commercial agendas: "I think it's useful for him to maintain a certain narrative that drives consumption of GPUs." Another distinguished between operational automation feasibility and strategic planning complexity: "There's an awful lot of standard automation that can be done... but to get to a point where you fit into process understanding... that's not feasible."

4.2. Resources and Capabilities Through the RBV Lens

4.2.1. Quantitative Assessment of AI Resources

Survey findings (visualized in Figure 3) revealed clear prioritization hierarchies among AI resources. Computational power emerged as a commodity resource (M=1.62, SD=1.16), with low strategic value indicating a "Buy" orientation through cloud providers. In contrast to this commoditized view of computational infrastructure, three core resources emerged as significant differentiators requiring a "Build" orientation.

Foremost among these strategic resources was proprietary data (M=3.81, SD=1.33), which respondents valued most highly due to its uniqueness and context-specificity. Similarly valued was human talent (M=3.68, SD=1.27), recognized for the specialized, tacit knowledge necessary to translate generic AI tools into strategic assets. AI governance (M=3.83, SD=1.36) was equally prioritized as a complex, organization-specific capability essential for building trust and ensuring responsible deployment.

However, despite the high perceived value of governance capabilities, current investment levels revealed concerning gaps (M=3.20, SD=1.06), though future investment intentions were notably stronger (M=3.88, SD=0.88). Algorithms occupied a middle position in the strategic hierarchy (M=3.07, SD=1.50), suggesting that their strategic value depends on integration with proprietary resources.

These perceptions translated into distinct investment priorities for the next 1-2 years, with data (M=3.75, SD=1.29) and human talent (M=3.54, SD=1.35) receiving clear emphasis. By comparison, computational power (M=2.54, SD=1.41) received lower priority, consistent with its commodity status. Notably, AI governance (M=2.89, SD=1.42) also received lower near-term investment priority despite its recognized long-term importance.

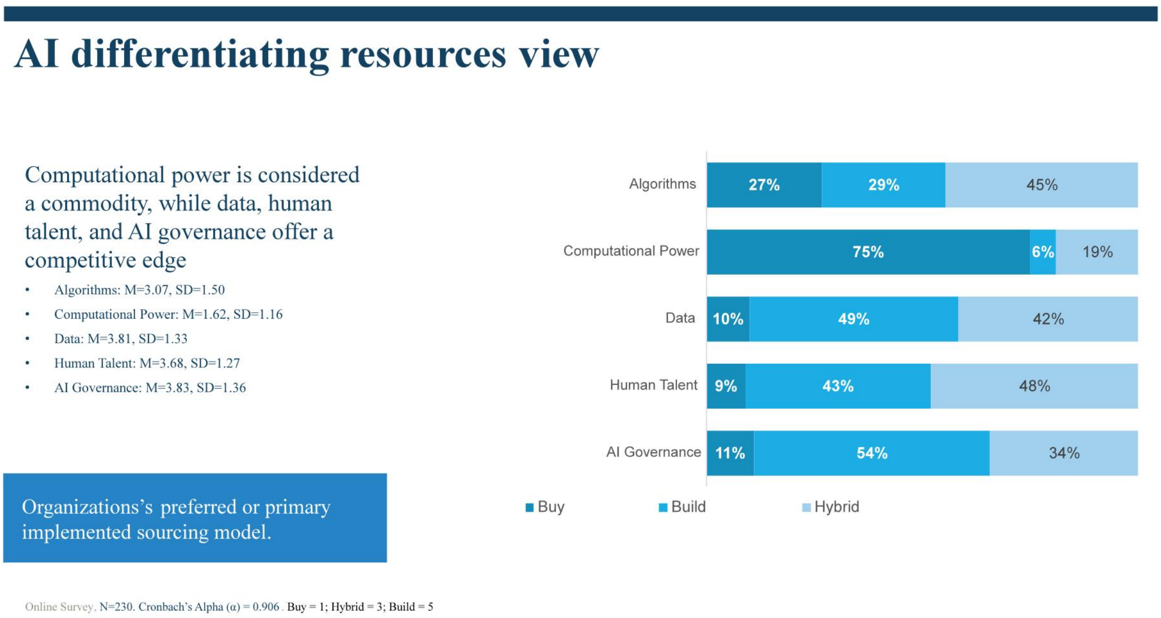

Figure 3. AI differentiating resources view

4.2.2. Qualitative Insights on Critical Capabilities

Expert interviews validated and elaborated upon these survey findings, providing deeper insight into how organizations approach these prioritized resources. Consistent with the high valuation of proprietary data in the survey results, data accessibility emerged as a foundational capability in the interviews. As one CIO emphasized: "It is data accessibility that is critical. We have structured governance to direct AI initiatives and ensuring data is accessible and of high quality."

However, interviews revealed a critical tension inherent in data management that the survey metrics alone could not capture: the competing imperatives of open knowledge sharing and proprietary data protection. One expert proposed radical accessibility, suggesting that "to achieve AI's Nirvana... we would have to create a world where we're accepting that our LLM knowledge can be publicly shared with anyone," while others emphasized protective approaches for maintaining competitive advantage. Accessing data resources proves insufficient without technical orchestration capabilities. Interviews iterated that organizations require unifying structured and unstructured data at scale, transforming core processes, and managing current AI limitations as hallucinations, unpredictable costs, and rapidly evolving models. Operational challenge as scalability concerns - “can technology support the volume? How would we be able to scale up?" - demonstrate why resource acquisition alone cannot guarantee strategic value

This tension helps explain why governance capabilities prove particularly complex in practice. The interviews illuminated specific governance challenges that account for the gap between perceived importance and current investment levels identified in the survey. Leadership disengagement emerged as a major barrier, with one expert noting "failure at the top" in understanding and embracing technology governance responsibilities. Effective governance requires dynamic capabilities: integrated feedback loops, adaptive compliance frameworks balancing ethical standards across jurisdictions, and continuous oversight mechanisms.

4.3. Human-AI Interaction Design

4.3.1. Survey Evidence on Collaboration Patterns

Survey respondents expressed cautiously optimistic yet constrained views regarding current human-AI collaboration. The majority acknowledged AI's potential to enhance human capabilities, particularly through "only when needed" support (M=3.81, SD=0.80), framing AI primarily as an augmentation tool rather than a true collaborative partner. The path toward deeper symbiotic relationships faces significant barriers, including ethical concerns (M=3.30, SD=1.04) and interaction difficulties, which tempered expectations for rapid evolution toward genuine human-AI symbiosis within 1-2 years (M=2.99, SD=1.09).

Despite these systemic barriers, practitioners demonstrated notably proactive stances toward individual skill development (M=3.99, SD=0.78), coupled with moderate confidence in interpreting AI outputs (M=3.48, SD=0.92). The progress toward enhanced capabilities is impeded by organizational resource constraints (M=3.43, SD=0.99), respondents expressed strong strategic commitment to future investments in human-AI capabilities (M=3.99, SD=0.89), with regression analysis revealing a significant predictive relationship between perceived AI effectiveness and future adoption intentions ($\beta=0.63$, $p<0.001$).

Trust-building initiatives, including transparent policies (M=3.47, SD=1.05) and ethical frameworks (M=3.61, SD=1.00), showed positive correlation with adoption rates ($r=0.43$, $p<0.01$). However, critical trust deficits persisted, particularly due to challenges in implementing effective audit mechanisms (M=3.40, SD=0.89) with trust concerns manifested by the overwhelming rejection of delegating accountability (see Figure 4) to AI systems (M=2.13, SD=1.01), reinforcing the continued requirement for human oversight.

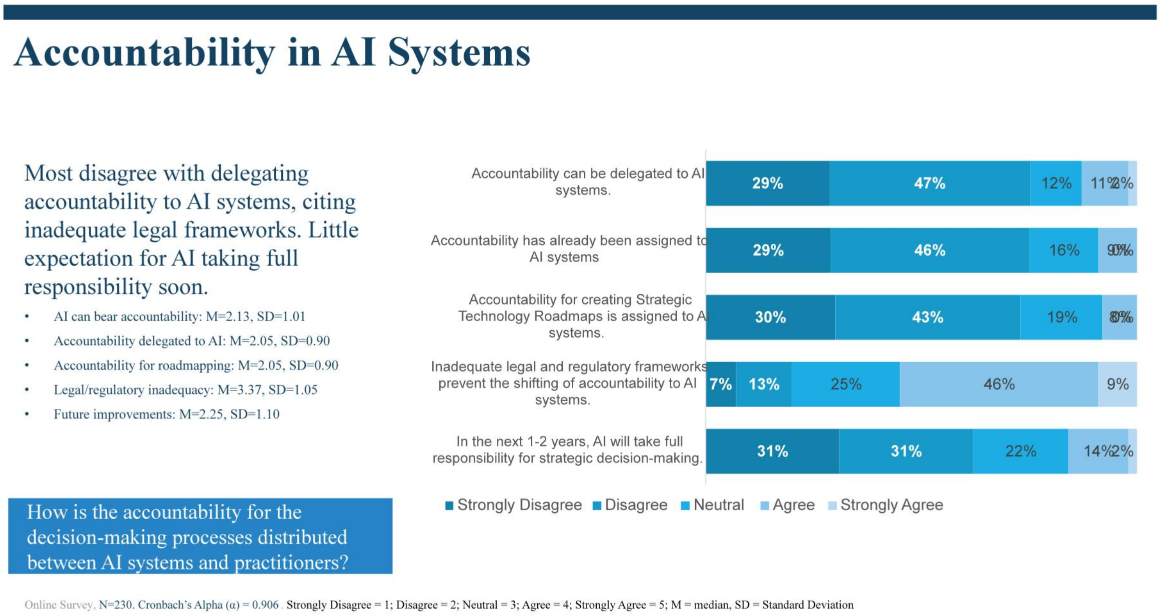

Figure 4. Accountability in AI Systems

4.3.2. Expert Views on Augmentation Models

Interview analysis reinforced the survey's positioning of AI as a strategic augmenter rather than replacement. Experts described AI's value in automating labor-intensive groundwork, with one noting that AI delivers "75-90% of drafting" while requiring human oversight for contextualization within organizational nuances and strategic intent. The interviews revealed that effective human-AI collaboration requires iterative co-creation. AI serves as a dynamic partner providing real-time insights and challenging assumptions, while humans refine direction and make final judgments.

The interviews elaborated on the trust concerns identified in the survey findings. AI "black box" nature creates fundamental barriers that transparent policies and ethical frameworks alone cannot fully resolve. Experts emphasized that building trust requires not only transparency and consistent performance but also user involvement in collaborative design. Organizations must focus on "celebrating successes" to build familiarity and confidence.

Interviewees conveyed that organizations must develop critical thinking competencies to evaluate AI outputs and formulate effective prompts. Successful AI-supported decision-making depends on "being able to articulate those [strategic] questions" to ensure AI responses align with organizational context and strategic objectives. The theme emerging from interview requires organizations moving beyond aspirational adoption toward evidence-based assessment of AI's impact on specific operational processes. Human expertise should be strategically reallocated from routine tasks toward complex decision-making activities that demand contextual judgment and strategic integration.

5. Discussion

5.1. RQ1: AI Innovation in STM Success Factors

The findings establish that AI fundamentally transforms two critical success factors for STM roadmap formulation under conditions of uncertainty and complexity.

First, AI enables a paradigm shift from intuition-based to evidence-based strategic alignment, providing data-driven insights that compel organizations to define clear business purposes and robust architectures before implementation. In this sense, AI acts primarily as a catalyst that forces strategic clarity rather than directly solving the alignment problem. AI's ability to process vast datasets and generate predictive insights addresses the long-standing challenge of cognitive bias in strategic planning. The correlation between AI's effectiveness in defining strategic actions and handling uncertainty demonstrates AI's potential for managing volatile environments. However, as the expert interviews reveal, this potential is realized only when organizations exhibit already the discipline and maturity necessary for pursuing strategic alignment.

Second, AI's ability to process high volumes of data at speed enables a shift from static STM roadmaps to continuous strategic planning - an "infinite game" approach fundamentally reconceptualizes STM, replacing rigid multi-year plans with fluid, adaptive frameworks.

However, significant limitations persist. Experts warn of a "mirage of alignment," where AI generates superficially impressive yet inauthentic strategies, underscoring the persistent importance of human judgment. The gap between AI's tactical strengths (Know WHAT/HOW) and strategic weaknesses (Know WHY/WHEN) requires human strategists to provide contextual intelligence and navigate organizational complexities beyond AI's grasp.

5.2. RQ2: Essential Resources and Capabilities

The research provides a comprehensive answer to the question of what resources and capabilities organizations require for AI-enhanced STM, revealing a clear hierarchy that challenges conventional assumptions about AI adoption. The findings definitively establish that competitive advantage derives not from technological resources themselves but from organization-specific capabilities to orchestrate the resources effectively.

The shift from technology to capability has concrete implications. Most notably, computational power - while necessary - has become commoditized and therefore strategically insignificant. The research suggests that organizations pursuing competitive advantage through computational accumulation are fundamentally misallocating resources, a finding that strikes with the current race to build powerful data centres (Kinder, 2025). Instead, the research identifies three categories of truly differentiating resources: proprietary data ecosystems, specialized human talent, and robust governance capabilities.

Among these differentiators, governance presents a particular paradox. Despite its recognized importance, it suffers from significant underinvestment, creating a substantial implementation gap deriving from leadership disengagement, rapidly evolving technology that outpaces governance frameworks, and the inherent difficulty of governing poorly understood systems. The urgency of addressing this implementation gap is amplified by governance's transition from competitive differentiator to regulatory prerequisite, as exemplified by the EU AI Act.

The data reveals a further disconnect between organizational perception and strategic reality. The surprising undervaluation of algorithms in both survey and interview contrasts sharply with the literature's emphasis on pre-trained domain models, suggesting organizations may be overlooking strategic opportunities in developing specialized algorithmic capabilities tailored to their specific contexts.

5.3. RQ3: Designing Human-AI Interaction

This research reveals that human-AI collaboration remains constrained by fundamental trust and transparency barriers rather than technological capability. The overwhelming rejection of AI accountability reflects persistent concerns about black box reasoning, inadequate audit mechanisms, and unclear ethical. While AI automates substantial groundwork, organizations refuse to delegate strategic authority, positioning AI strictly as an augmentation tool rather than collaborative partner.

The gap between individual skill development and organizational investment signals a fundamental misalignment: AI integration is treated as a competency problem rather than systemic transformation. Effective collaboration demands reconstructing how organizations allocate cognitive labor and developing capabilities to formulate strategic questions that align AI outputs with organizational context. The predictive relationship between perceived effectiveness and adoption intentions reveals that transformation emerges through experiential learning rather than advance planning, requiring iterative capability reconfiguration rather than predetermined implementation strategies.

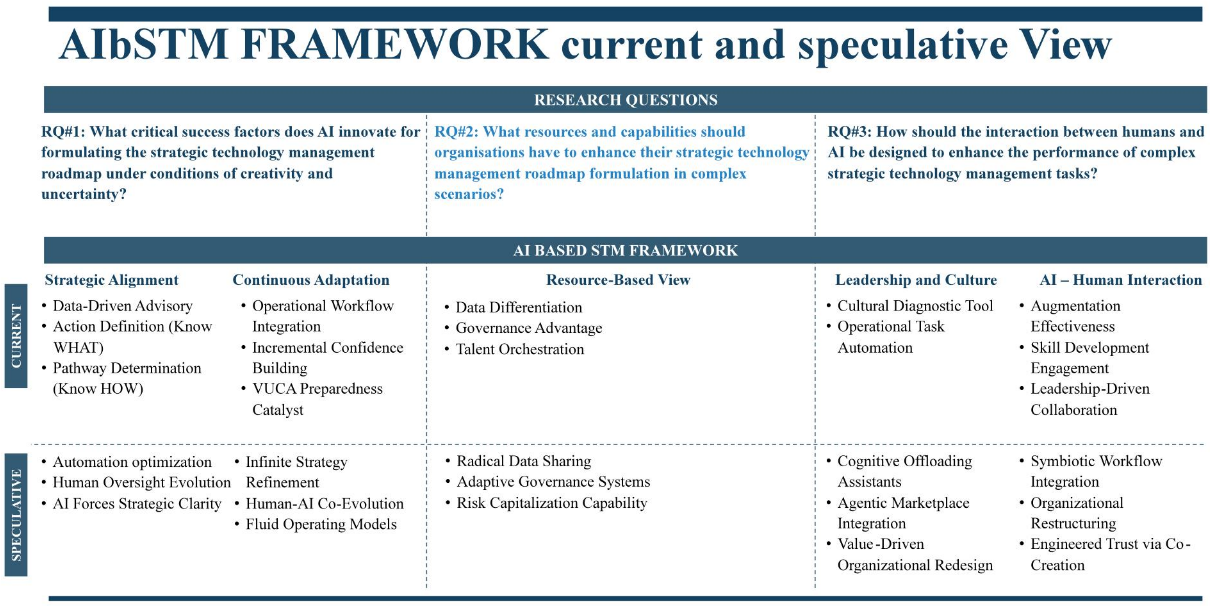

Figure 5. AIbSTM Framework highlighting the current practices across each dimension of the framework and the speculative view for evolutionary directions

5.4. Synthesis and Implications

The AIbSTM framework, visualized in Figure 5, synthesises the insights emerged in the discussion by providing both theoretical advancement and practical guidance. Its three-layered structure - strategic alignment/continuous adaptation, resource-based view, and leadership/culture/interaction - maps directly onto the research questions while offering actionable pathways for implementation. The framework's value lies not just in describing current practices but in prescribing the organizational transformations necessary for successful AI integration.

6. Contribution and Limitations

6.1. Theoretical and Practical Contributions

The research advances Resource-Based View theory by demonstrating that AI-driven competitive advantage derives not from computational resources - which are increasingly commoditized - but from organization-specific capabilities in data governance, specialized talent development, and ethical AI leadership. The study establishes governance frameworks and dynamic leadership as critical theoretical constructs, addressing both the socio-technical chasm (trust, cultural readiness) and the cognitive chasm (human judgment versus algorithmic processing) that impede AI value realization. By reconceptualizing AI integration as a capability-building effort requiring symbiotic human-AI collaboration, the research extends RBV beyond traditional resource acquisition toward dynamic capability cultivation.

The AIbSTM framework synthesizes these theoretical insights into actionable guidance through its three-layered structure: strategic alignment enabling continuous adaptation through real-time analytics; resource orchestration; and human-AI interaction design preserving human judgment while leveraging AI's analytical power. The framework practical value extends beyond prescriptive guidance by enabling organizational self-assessment. Using the conceptual framework checklist in Appendix A, leaders can evaluate their organization's AI readiness across multiple dimensions, identify capability gaps, and prioritize interventions that ensure AI investments yield strategic rather than merely tactical value.

6.2. Limitations

This study acknowledges some methodological limitations. The convenience and snowball sampling via LinkedIn may introduce selection bias toward technology-forward professionals. The cross-sectional design captures a single snapshot of rapidly evolving AI practices, precluding longitudinal examination of how trust, capabilities, and structures develop over time. While the qualitative sample (n=14) provides rich insights, its size limits generalizability may underrepresent critical perspectives. Self-reported survey data also presents potential response bias. These limitations were addressed through mixed-methods triangulation and transparent acknowledgment in interpreting findings.

7. Conclusion

This research establishes a comprehensive framework for understanding AI's transformative impact on strategic technology management. Addressing the persistent challenge of underperforming technology investments, the study demonstrates that AI's value lies not in automating strategy but in catalysing organizational transformation. The rejection of autonomous AI leadership in favor of human-centric augmentation represents a crucial finding with immediate practical implications.

The journey toward AI-enhanced strategic technology management requires continuous co-evolution between human and artificial intelligence rather than linear technological progress. Organizations must focus not on replacing human judgment but on creating synergetic relationships where AI's analytical power complements human creativity, contextual intelligence, and ethical reasoning. The introduced AIbSTM framework's provides both theoretical advancement and practical guidance for integrating AI into strategic decision-making in ways that enhance rather than diminish human contribution to organizational success.

Appendix A. Checklist and speculating view for the AIbSTM conceptual framework dimensions for AI facilitating STM

<table>
<tr><th colspan="2">Strategic Alignment</th></tr>
<tr><td rowspan="3">Observed behaviours and checklist</td><td>Data-Driven Leadership Advisory - AI provides insights to leadership, informing strategy decisions through analysed data.
Validated by AI-powered drafted strategy: using generative AI to streamline initial strategic planning and documentation. This includes crafting tailored strategies, goals, and objectives based on user input, which allows for more adaptable workflows and cross-verification of information.</td></tr>
<tr><td>Action Definition (Know WHAT) - AI identifies specific strategic actions needed based on analysis.
Validated by Scenario simulation: simulate scenarios like market shifts and competitor actions to make strategies more adaptable and proactively test strategic options.</td></tr>
<tr><td>Pathway Determination (Know HOW) - AI outlines implementation methods and technological pathways for strategic initiatives.
Validated by Automated portfolio management: enablement of [or deployment of tools to provide] AI based support portfolio management by providing real-time insights, modelling what-if scenarios, and optimizing portfolios for strategic prioritization.</td></tr>
<tr><td rowspan="2">Speculating – how AI could support higher strategic alignment</td><td>Agentic CTO Evaluation - AI autonomously performing core CTO functions (strategy synthesis, roadmap creation). More feasible for specific hierarchical/digital-native cultures with low ethical constraints.</td></tr>
<tr><td>Human Oversight Evolution - Human roles shift from direct control to phased supervision of AI agents. Requires structured roadmaps (from controls to supervision) and tolerates non-</td></tr>
</table>

	linear progression.
	AI Forces Strategic Clarity - AI reinforcing unprecedented precision in business purpose, objectives, and translation to technology. Still success depends on robust organization' business architecture and overcoming measurement.
Continuous Adaptation	
Observed behaviours and checklist	Operational Workflow Integration - AI effectively handles routine tasks, establishing a foothold in daily processes despite strategic hesitancy. Validated by Integrate AI into Workforce Planning: using AI for scenario planning to anticipate skill gaps, automate talent allocation, and identify reskilling pathways.
	Incremental Confidence Building - Gradual AI adoption in low-risk areas fosters organizational trust for future strategic scaling. Validated by Integrate Human-AI Bidirectional Learning: creating a continuous feedback loop where AI adapts to human feedback, and humans adjust to AI insights.
	VUCA Preparedness Catalyst - AI enables early-stage volatility monitoring, providing data-driven signals for proactive adaptation. Validated by Integrate Dynamic What-if Scenarios: using AI to model and test strategic options, ensuring continuous adaptation to market and competitor changes.
Speculating – how AI could define and facilitate continuous adaptation	Infinite Strategy Refinement - AI could enable real-time roadmap updates weekly/monthly. Requires human oversight to prevent "superficial outputs".
	Human-AI Co-Evolution - AI as symbiotic partner navigating VUCA uncertainties. "Cultural inertia" may obstruct equitable collaboration.
	Fluid Operating Models - Self-adjusting workflows where AI reconfigures strategies dynamically. Demands "structured change management" to avoid tool redundancy.
Resource-Based View	
Observed behaviours and checklist	Data Differentiation - Proprietary data is leveraged as a rare, valuable asset for unique AI insights, enabling competitive differentiation. Validated by Integrate AI Resources and Capabilities Checklists: to evaluate the key resources and capabilities as proprietary data ecosystems, specialized human talent, and robust governance capabilities.
	Governance Advantage - Robust AI governance is a non-substitutable capability building trust, mitigating unique risks, and enabling responsible, strategic AI deployment. Validated by AI Governance model: to manage data workflows and establish ethical frameworks, roles, and compliance.
	Talent Orchestration - Specialized human talent possesses tacit knowledge crucial for

	contextually developing, deploying, and managing AI effectively within the organization. Validated by Hybrid Talent model: integrate "fusion" skills with AI capabilities for strategic alignment.
Speculating – what new resources will determine a competitive advantage in an AI driven STM	Radical Data Sharing - Public sharing of proprietary data/knowledge (e.g., "publicly shared LLM knowledge") could unlock unprecedented AI value, redefining exclusivity. This requires balancing conservative views who fiercely protect proprietary data ("very protective") as a core strategic asset.
	Adaptive Governance Systems - Dynamic, embedded feedback loops and "polished frameworks" will continuously evolve governance, replacing static compliance. Requires overcoming leadership disengagement ("failure at the top") and ethical ambiguity for effective implementation.
	Risk Capitalization Capability - Organizations will strategically cultivate "healthy risk appetite" as a core capability, tolerating operational risk for speed/innovation. Must rigorously balance this with mitigating existential threats (e.g., breaches, reputational damage) highlighted as critical.
Leadership and Culture	
Observed behaviours and checklist	Cultural Diagnostic Tool - AI monitors organizational culture, identifies alignment/friction points via sentiment analysis. Validated by Culture and Leadership Diagnostic Tool: assess and guide organizational culture and leadership to effectively manage AI integration and human-AI interactions.
	Operational Task Automation - AI handles routine operational "dirty work", freeing human capacity for higher-value activities. Validated by Value Creation guidelines: define the value tree, linking business objectives to measurable key performance indicators (KPIs).
Speculating – how AI could change strategic technology leadership and culture	Cognitive Offloading Assistants - AI as "digital mentors/coaches" elevating human work. Requires workflow redesign to prevent value loss.
	Agentic Marketplace Integration - Marketplaces enable accessible AI agents for task execution. It requires managing "Extremely messy" unvetted agents risk ethics/alignment.
	Value-Driven Organizational Redesign - AI enables human-AI workflows focusing talent on strategy. It requires managing resistance to structural change hinders adoption.
AI – Human Interaction	
Observed behaviours and checklist	Augmentation Effectiveness - AI successfully automates groundwork (data/code generation), freeing humans for strategy/validation. Validated by Design for co-creation: design for co-creation cycles, explanatory dialogues, and verification mechanisms, positioning AI as a collaborative partner.
	Skill Development Engagement - High practitioner upskilling activity driven by leadership

	mandates on critical AI competencies. Validated by Establish human judgment checkpoints: preserve human expertise by creating verification points for AI-generated outputs.
	Leadership-Driven Collaboration - Leaders actively promote AI-human collaboration to boost decision-making performance in specific workflows. Validated by Checklist for AI-Assisted Decision Making: integrate AI to mitigate human bias, enhance foresight, and improve strategic decision-making. It should include validation for Bias Mitigation; Enhanced Foresight; Data and Insights; Interactive Loop; Dynamic Roadmaps.
Speculating – how AI and human will engage in an AI driven STM	Symbiotic Workflow Integration - AI evolves into a dynamic co-creator, providing real-time insights and challenging assumptions iteratively within tasks. It requires removing ethical and trust barriers.
	Organizational Restructuring - Shift to "diamond-shaped" teams with AI agents handling execution, reducing low-level roles and enabling fractional leadership. It requires moving [partial] accountability from human to machine developing new legal frameworks covering AI responsibility.
	Engineered Trust via Co-Creation - Trust built through explainable AI, low-risk pilots, user co-design, and celebrating joint successes to overcome "black box" fears. It requires reducing effectiveness gaps; and to address ethics concerns reducing trust.

Author Contributions:

Conceptualization, Massimo Fascinari; methodology, Massimo Fascinari; software, not applicable; validation, Vincent English; formal analysis, Massimo Fascinari; investigation, Massimo Fascinari; resources, Massimo Fascinari; data curation, Massimo Fascinari and Vincent English; writing—original draft preparation, Massimo Fascinari; writing—review and editing, Massimo Fascinari; visualization, Massimo Fascinari; supervision, Vincent English; project administration, Massimo Fascinari; funding acquisition, not applicable. All authors have read and agreed to the published version of the manuscript.

Funding:

This research received no external funding.

Institutional Review Board Statement:

This study was approved by the Telematic University UNINETTUNO (TUU) Ethics Committee and conducted in accordance with its guidelines.

Informed Consent Statement:

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement:

The raw data supporting the conclusions of this article will be made available by the corresponding author on request.

Acknowledgments:

A special acknowledgment is due to the Telematic University UNINETTUNO (TUU) for providing institutional support.

Conflict of Interest:

The authors declare no conflict of interest.

References

Abdullah, A.-N. (2025). The intersection of AI and strategy: Navigating challenges and opportunities. International Journal of Advanced Research in Computer and Communication Engineering, 14, 13-30.

Accenture. (2025). Technology vision 2025. Accenture.

Agarwal, A. (2025). Optimizing employee roles in the era of generative AI: A multi-criteria decision-making analysis of co-creation dynamics. Cogent Social Sciences, 11(1), 2476737.

Banh, L., et al. (2025). Copiloting the future: How generative AI transforms software engineering. Information and Software Technology, 183, 107751.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. Journal of Management, 27(6), 643–650.

Bilal, A., et al. (2025). LLMs for explainable AI: A comprehensive survey. arXiv. https://arxiv.org/abs/2504.00125

Biloslavo, R., Edgar, D., Aydin, E., & Bulut, C. (2024). Artificial intelligence (AI) and strategic planning process within VUCA environments: A research agenda and guidelines. Management Decision, 63(10), 3599-3624.

Borkovich, D. J., et al. (2015). New technology adoption: Embracing cultural influences. Issues in Information Systems, 16(3), 138-147.

Chernov, A. V., et al. (2020). The usage of artificial intelligence in strategic decision making in terms of the fourth industrial revolution. In Proceedings of the 1st International Conference on Emerging Trends and Challenges in the Management Theory and Practice (ETCMTP 2019). Atlantis Press. https://doi.org/10.2991/aebmr.k.200229.031

Čižo, E., et al. (2025). Information technology/artificial intelligence use and labor productivity in firms. Journal of Entrepreneurship and Sustainability Issues, 12(4), 232-250.

Collins, K. M., et al. (2025). Revisiting Rogers′ paradox in the context of human–AI interaction. arXiv. https://arxiv.org/abs/2501.10476

Creswell, J. W. (2021). A concise introduction to mixed methods research. Sage.

D′Amico, A., Hazan, E., Tricoli, A., & Montard, A. (2025). How AI is transforming strategy development. McKinsey & Company.

Daskalopoulos, E. T., & Machek, O. (2025). Shaping ambidextrous organisations through AI and decision-making: A distinct path for family firms? Journal of Family Business Management. Advance online publication.

Davenport, T. H. (2021). Enterprise adoption and management of artificial intelligence. Management and Business Review, 1(1), 1–9.

Dell'Acqua, F., et al. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. Harvard Business School Working Paper, No. 24-013.

Deutsch, N., & Berényi, L. (2023). Technology and strategy: Towards strategic techno-management. Theory, Methodology, Practice, 19, 41–51.

Diyin, Z., & Bhaumik, A. (2025). The impact of artificial intelligence on business strategy: A review of theoretical and empirical studies in China. International Journal of Advances in Business and Management Research, 2(3), 9–17.

Eriksson, T., et al. (2020). Think with me, or think for me? On the future role of artificial intelligence in marketing strategy formulation. The TQM Journal, 32(4), 795–814.

Floridi, L. (2023). The ethics of artificial intelligence: Principles, challenges, and opportunities. Oxford University Press.

Floridi, L., et al. (2025). Open-source AI made in the EU: Why it is a good idea. Minds and Machines, 35(2), 23–41.

Galloway, S. (2024). Corporate Ozempic. Medium. https://medium.com/@profgalloway/corporate-ozempic-da829480c878

Haefner, N., et al. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. Technological Forecasting and Social Change, 162, 120392.

Handa, K., et al. (2025). Which economic tasks are performed with AI? Evidence from millions of Claude conversations. arXiv. https://arxiv.org/abs/2503.04761

Holmström, J., & Carroll, N. (2025). How organizations can innovate with generative AI. Business Horizons, 68(5), 559–573.

IBM. (2025). The ingenuity of generative AI. IBM Institute for Business Value.

Jones, R. M., & Wray, R. E. (2006). Comparative analysis of frameworks for knowledge-intensive intelligent agents. AI Magazine, 27(2), 57.

Kaplan, J., et al. (2020). Scaling laws for neural language models. arXiv. https://arxiv.org/abs/2001.08361

Kesting, P. (2024). How artificial intelligence will revolutionize management studies: A Savagean perspective. Scandinavian Journal of Management, 40(2), 101330.

Kharbanda, V. P. (2001). Strategic technology management and international competition in developing countries: The need for a dynamic approach. Journal of Scientific and Industrial Research, 60, 291–297.

Kinder, T. (2025). Tech groups shift $120bn of AI data centre debt off balance sheets. Financial Times.

Kokotajlo, D., et al. (2025). AI 2027. https://ai2027.com

Krishnan, N. (2025). AI agents: Evolution, architecture, and real-world applications. arXiv. https://arxiv.org/abs/2503.12687

Krishnan, S., et al. (2019). Artificial intelligence in resource-constrained and shared environments. ACM SIGOPS Operating Systems Review, 53(1), 1–6.

Kumar, R., et al. (2025). LLM-powered knowledge graphs for enterprise intelligence and analytics. arXiv. https://arxiv.org/abs/2503.07993

Kurzhals, C., et al. (2020). Strategic leadership and technological innovation: A comprehensive review and research agenda. Corporate Governance: An International Review, 28(6), 437–464.

Lee, H.-P., et al. (2025). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. In Proceedings of the CHI Conference on Human Factors in Computing Systems.

Li, K. (2025). Strategic management practices in Chinese enterprises under the influence of artificial intelligence. Development of Humanities and Social Sciences, 1(2), 72–94.

Li, Y., et al. (2024). Developing trustworthy artificial intelligence: Insights from research on interpersonal, human-automation, and human–AI trust. Frontiers in Psychology, 15, 1382693.

Lu, C., et al. (2024). The AI scientist: Towards fully automated open-ended scientific discovery. arXiv. https://arxiv.org/abs/2408.06292

Mäkelä, E., & Stephany, F. (2024). Complement or substitute? How AI increases the demand for human skills. arXiv. https://arxiv.org/abs/2412.19754

Massoudi, A. H., et al. (2024). The role of artificial intelligence application in strategic marketing decision-making process. Cihan University–Erbil Journal of Humanities and Social Sciences, 8(1), 34–39.

Meer, J. B. van der, & Calori, R. (1989). Strategic management in technology-intensive industries. International Journal of Technology Management, 4(2), 127–139.

Mei, Z., et al. (2025). Reasoning about uncertainty: Do reasoning models know when they don’t know? arXiv. https://arxiv.org/abs/2506.18183

Naqvi, A. (2017). Responding to the will of the machine: Leadership in the age of artificial intelligence. Journal of Economics Bibliography, 4(3), 244–248.

National Research Council. (1987). Management of technology: The hidden competitive advantage. National Academies Press.

NVIDIA. (2025). NVIDIA CEO Jensen Huang keynote at CES 2025.

Owusu, J., & Agbesi, I. S. (2025). Navigating the dilemma of AI integration for organisational performance: Insights for contemporary business strategists. Pan-African Journal of Education and Social Sciences, 6(1), 49–62.

Perifanis, N.-A., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. Information, 14(2), 85.

Purdy, M., & Williams, A. (2023). How AI can help leaders make better decisions under pressure. Harvard Business Review, 1–10.

Roberts, E. B. (2001). Benchmarking global strategic management of technology. Research-Technology Management, 44(2), 25–36.

Rowe, F., et al. (2024). Beliefs, controversies, and innovation diffusion: The case of generative AI in a large technological firm. In Proceedings of DIGIT 2024. Bangkok, Thailand.

Sahlman, K., & Haapasalo, H. (2009). Elements of strategic management of technology: A conceptual framework of enterprise practice. International Journal of Management and Enterprise Development, 7, 10–32.

Sands, D. E. (1991). Effective strategic management for technology-based firms: Context, management style, and incentives. Technology Management: The New International Language.

Saunders, M., & Lewis, P. (2017). Doing research in business and management. Pearson.

Schrage, M., et al. (2024). The future of strategic measurement: Enhancing KPIs with AI. Future.

Simkute, A., et al. (2024). Ironies of generative AI: Understanding and mitigating productivity loss in human–AI interactions. arXiv. https://arxiv.org/abs/2402.11364

Singh, A., et al. (2025). Enhancing critical thinking in generative AI search with metacognitive prompts. arXiv. https://arxiv.org/abs/2505.24014

Stegman, E., et al. (2023). IT key metrics data 2024: Industry measures—Strategic investments & business outcomes. Gartner.

Tashakkori, A., & Teddlie, C. (2010). Putting the human back in human research methodology: The researcher in mixed methods research. Journal of Mixed Methods Research, 4(4), 271–277.

Teece, D. J., et al. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Wernerfelt, B. (1984). A resource-based view of the firm. Strategic Management Journal, 5(2), 171–180.

Woodruff, A., et al. (2024). How knowledge workers think generative AI will (not) transform their industries. In Proceedings of the CHI Conference on Human Factors in Computing Systems.

Wu, S., et al. (2025). Human–generative AI collaboration enhances task performance but undermines human's intrinsic motivation. Scientific Reports, 15(1), 15105.

Yun, B., et al. (2025). Generative AI in knowledge work: Design implications for data navigation and decision-making. In Proceedings of the CHI Conference on Human Factors in Computing Systems.