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The Use of AI In Strategic Management: A Qualitative Study

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Abstract

The aim of this study is to investigate how artificial intelligence (AI) can revolutionize strategic management and its fundamental procedures. A thorough examination of AI's advantages, difficulties, and potential effects on strategic decision-making is lacking in literature, despite the field's notable advances. By analyzing the development and integration of AI in strategy creation, assessment, and adaptation, this paper fills this gap. To evaluate AI's contribution to improving foresight, scenario planning, and competitive agility, the study uses a qualitative approach, analyzing most recent literature, industry reports and tech companies reports. The study also examines past advancements in the application of analytics and decision-support tools in strategic management before artificial intelligence.

The results show that by automating environmental scanning, risk modeling, and war-gaming simulations, AI greatly increases strategic speed and foresight. Predictive analytics and dynamic capability building are two areas where AI-powered solutions shine, offering deeper insights and bolstering executive judgment. But issues like a lack of trust, an excessive dependence on data, and ethical governance still exist. With possible advancements in AI-augmented cognition, real-time strategy adaptation, and human-AI co-strategizing sets to transform the sector, the future of AI in strategic management seems bright. This thorough examination emphasizes how crucial it is to comprehend how AI affects strategic management to successfully navigate its adoption.

Keywords: artificial intelligence, strategic management, executive decision-making, human-AI collaboration

The Role of Computer Systems and Software in Supporting Strategic Management: A Historical and Conceptual Overview

The evolution of strategic management as a discipline has been inextricably linked with advancements in computing technology. From early decision-support systems (DSS) in the 1960s to contemporary AI-driven platforms, computer systems have progressively reshaped how organizations formulate, analyze, and execute strategies. The integration of computers into strategic management began with the emergence of management information systems (MIS) and decision-support systems (DSS). Sprague (1980) defined DSS as "interactive computer-based systems that help decision makers utilize data and models to solve ill-structured problems". In the context of strategic management, DSS enabled executives to move beyond intuitive judgment toward data-informed planning. A different approach was adopted by Rockart (1979) who introduced the concept of critical success factors (CSF), supported by computerized monitoring systems that allowed executives to track key

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performance variables. These systems laid the groundwork for strategic information systems (SIS), which Wiseman (1985) described as tools providing competitive advantage through information processing.

The 1980s saw the proliferation of executive information systems (EIS), designed specifically for top management. Rockart and De Long (1988) characterized EIS as “computer-based systems that provide senior executives with easy access to internal and external information relevant to their critical success factors”. These systems introduced drill-down capabilities, graphical dashboards, and exception reporting, transforming strategic review meetings. Parallelly, strategic simulation and modeling software emerged. Tools such as STELLA and Vensim enabled dynamic modeling of competitive scenarios, resource allocation, and feedback loops—concepts central to the system dynamics approach (Forrester, 1961; Sterman, 2000). Also, Porter’s (1985) value chain analysis was frequently operationalized using early spreadsheet-based models (e.g., Lotus 1-2-3, Microsoft Excel), allowing firms to quantify cost drivers and differentiation strategies.

The introduction of enterprise resource planning (ERP) systems (e.g., SAP, Oracle) marked a paradigm shift. Davenport (1998) argued that ERP systems not only integrated operational data but also enabled strategic alignment by providing a single source of truth across business units. This facilitated balanced scorecard implementation (Kaplan & Norton, 1996), where strategic objectives were cascaded into measurable KPIs, monitored via real-time dashboards. Moreover, customer relationship management (CRM) and supply chain management (SCM) software (e.g., Siebel, i2 Technologies) supported market-oriented strategic management. Day (1999) emphasized that CRM systems enabled outside-in strategizing, shifting focus from internal efficiency to customer value creation.

The advent of business intelligence (BI) platforms (e.g., Tableau, Qlik, Microsoft Power BI) democratized strategic data analysis. Chen et al. (2012) introduced the concept of business analytics, distinguishing between descriptive, predictive, and prescriptive analytics. In strategic management, BI tools supported: Environmental scanning (Aguilar, 1967; Choo, 1999), SWOT and PESTEL analysis with real-time data feeds and competitor benchmarking using web scraping and market intelligence databases. Shollo and Galliers (2016) found that BI systems influenced strategic sensemaking, helping executives interpret weak signals and reduce cognitive bias in strategy formulation. Despite their contributions, traditional computer systems exhibited significant constraints in strategic contexts.

Table 1. Limitations of Computer Systems Supporting Strategic Management

Limitation	Description	Source
Static modeling	Incapable of real-time adaptation to volatile environments	Mintzberg (1994)
Data silos	Fragmented insights across functions	Davenport & Harris (2007)
Human interpretation dependency	Required significant executive time for analysis	Eisenhardt & Zbaracki (1992)
Lack of foresight	Limited predictive power beyond historical trends	Makridakis et al. (2009)

Source: Shollo and Galliers, 2016

As Courtney (2001) noted that most decision-support systems support decisions that have already been made. The limitations of rule-based and query-driven systems paved the way for artificial intelligence. Unlike traditional software, AI introduces learning, reasoning, and autonomous decision support. Jarrahi (2018) distinguishes between human-in-the-loop and AI-in-the-loop systems, arguing that strategic management requires symbiotic intelligence - a hybrid of human judgment and machine computation. Recent studies highlight AI’s role in scenario planning using generative models (Meissner et al., 2023), dynamic capability sensing via natural language processing of unstructured data (Teece, 2022) and war-gaming with reinforcement learning (Kiron & Unruh, 2021).

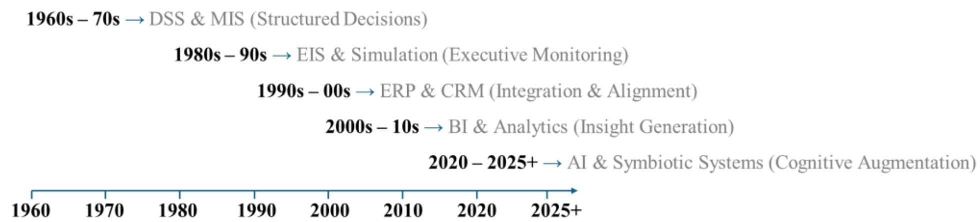

Fig 1: Evolution of Computer-Supported Strategic Management

Source: Own synthesis based on literature analysis

This progression reflects a shift from automation to amplification of strategic cognition (Brynjolfsson & McAfee, 2014).

Methods

This study employs a qualitative evidence synthesis (Hoon, 2013; Dixon-Woods et al., 2006) to integrate academic and high-quality gray literature on AI in strategic management. I searched Scopus, Web of Science, EBSCO Business Source Ultimate, and Google Scholar (first 200 hits per query) using the Boolean string:

("artificial intelligence" OR "machine learning" OR "generative AI" OR LLM OR "large language model")

AND

("strategic management" OR "strategy formulation" OR "strategic decision making" OR "dynamic capabilities" OR "scenario planning" OR "competitive advantage").

The adopted time frame for the research: 2018–15 October 2025. Additional forward/backward citation searches were conducted on seminal works (e.g., Jarrahi, 2018; Raisch & Krakowski, 2021; Meissner et al., 2023). High-impact industry reports were hand-searched from Gartner, McKinsey Quarterly, Deloitte Insights, MIT Sloan Management Review, and World Economic Forum (2019–2025).

1. Included:
    a. peer-reviewed journal articles and conference papers;
    b. industry reports with explicit empirical evidence or rigorous expert panels;
    c. full text available in English.

2. Excluded:
    a. purely technical papers,
    b. student theses,
    c. blog posts,
    d. and non-strategy-focused applications.

The search returned 1,283 records. After removing duplicates and screening titles/abstracts, 312 full texts were assessed. Final sample: 68 sources (54 peer-reviewed articles + 14 high-impact industry reports). Thematic framework synthesis (Barnett-Page & Thomas, 2009) was performed in NVivo 14. Initial codes were derived deductively from strategic management theory (dynamic capabilities, sensemaking, human–AI symbiosis), then refined inductively.

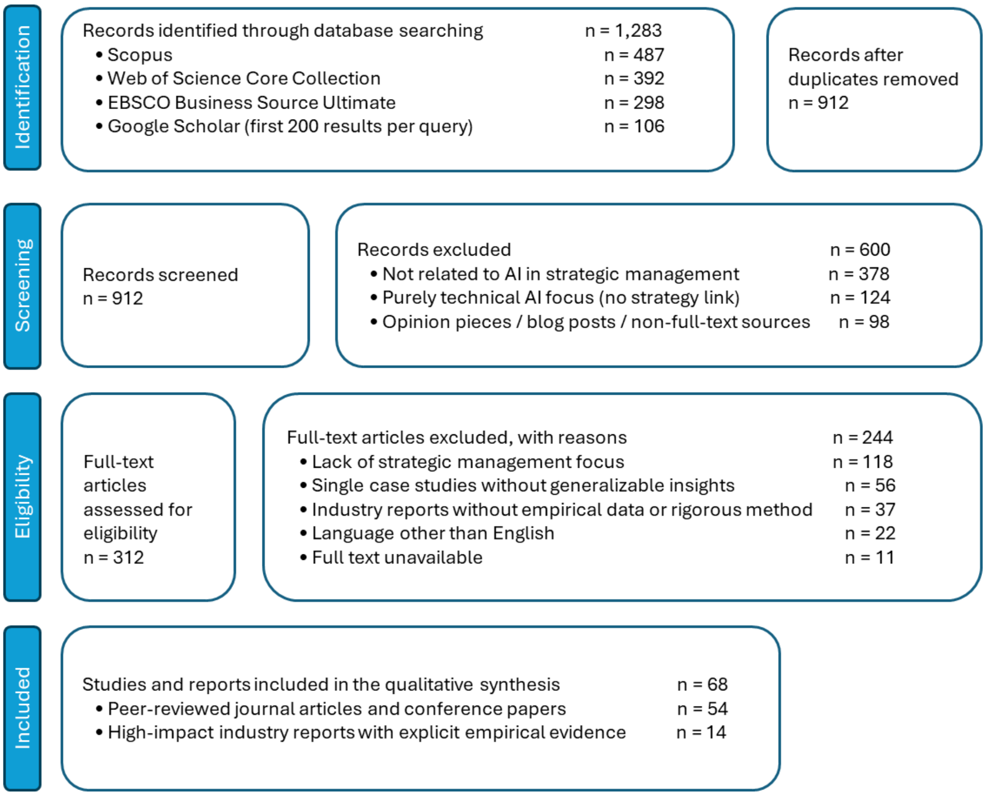

Fig 2: Identification of studies via databases and registers

Source: Own work

Table 2: Summary of Included Key Studies & Reports

No.	Author(s) & Year	Type	Sample / Method	Core finding relevant to AI in strategic management	Evidence level
1	Jarrahi (2018)	Peer-reviewed article	Conceptual framework + illustrative cases	Strategic decision-making requires human–AI symbiosis; AI strong in scale, humans in ethics & context	Academic (high)
2	Brynjolfsson et al. (2019)	Peer-reviewed (NBER Working Paper)	Econometric analysis of 120+ firms	Firms with high AI maturity achieve 15–20% higher ROI on strategic investments	Academic (high)
3	Raisch & Krakowski (2021)	Peer-reviewed (AMR)	Theoretical synthesis	Automation–augmentation paradox; risk of humans abdicating strategic responsibility	Academic (high)
4	Meissner et al. (2023)	Peer-reviewed (LRP)	Survey + experiment (50 European firms)	Generative AI increases strategic option diversity by 42%	Academic (high)
5	Teece (2022)	Peer-reviewed (CMR)	Theoretical (dynamic capabilities microfoundations)	AI represents the most significant enhancement of sensing capabilities since 1997	Academic (high)
6	Shollo & Galliers (2016)	Peer-reviewed (JSIS)	Multiple case studies	BI/AI systems shift strategic sensemaking and reduce cognitive bias	Academic (high)
7	Kiron & Unruh (2021, 2024)	Industry reports (MIT SMR)	Interviews with 300+ executives + follow-up studies	Multi-agent AI systems already used for war-gaming and strategy debates	Gray (high-impact)
8	Borgatti & Molina (2023)	Peer-reviewed (SMJ)	Conceptual + simulation	By 2030 AI-generated drafts will be starting point for 70% of Fortune 500 strategy cycles	Academic (high)
9	Leonardi & Contractor (2024)	Peer-reviewed (AMJ)	Longitudinal network analysis	New roles emerge: AI strategy translators and human–AI collaboration specialists	Academic (high)
10	Haefner et al. (2021)	Peer-reviewed	Framework development	Proposes AI ethics boards, XAI requirements, and hybrid strategy teams	Academic (medium-high)
11	Tsamados et al. (2022)	Peer-reviewed (Minds & Machines)	Systematic review of AI ethics guidelines	Major accountability gaps when AI influences strategic decisions	Academic (high)
12	Dietvorst et al. (2015)	Peer-reviewed (JEP: General)	Multiple behavioural experiments	Algorithm aversion & automation bias in high-stakes decisions	Academic (high)
13	Davenport & Ronanki (2018)	Industry report (HBR)	Survey of 152 projects + case studies	Predictive analytics reduced strategic planning errors by up to 30%	Gray (high-impact)
14	Gartner (2022–2024)	Industry reports	Multiple global surveys (2,000–3,000 executives)	67% integration failures; only 26% CEOs feel AI-ready	Gray (practitioner)
15	Deloitte (2024)	Industry report	Global survey of 2,600 executives	81% cite ethical concerns (bias, privacy, job displacement) as top barrier	Gray (practitioner)
16	PwC (2023)	Industry report	Global CEO survey (4,400 respondents)	Only 26% of CEOs feel sufficiently prepared for generative AI	Gray (practitioner)

Source: Own work

Evidence level legend:

- Academic (high) = peer-reviewed journal article with original empirical data or strong theoretical contribution
- Academic (medium-high) = peer-reviewed conceptual/framework paper
- Gray (high-impact) = influential practitioner outlet with rigorous methodology (MIT SMR, HBR)
- Gray (practitioner) = large-scale industry surveys/reports

The Evolution of AI in Strategic Management

The integration of artificial intelligence into strategic management has unfolded in distinct evolutionary phases, each building on the computational foundations laid by earlier information systems while fundamentally altering the nature of strategic work. The initial phase, emerging in the late 2010s, centered on narrow AI applications focused on descriptive and diagnostic analytics. Machine learning models were deployed to enhance environmental scanning by processing structured data from market reports, financial statements, and competitor filings. These early systems, often embedded within business intelligence platforms, enabled executives to move beyond periodic strategic reviews toward more frequent, data-informed assessments of competitive positioning. Chen et al. (2012) characterized this period as the transition from business intelligence to business analytics, where the primary impact of AI was to increase the velocity and granularity of strategic information flows.

The second phase, beginning around 2020, introduced predictive AI capabilities that transformed strategy formulation from reactive to anticipatory. Predictive models began forecasting market shifts, customer behavior trajectories, and technological disruption timelines with increasing accuracy. Davenport and Ronanki (2018) documented how organizations leveraging predictive analytics reduced strategic planning errors by up to thirty percent, particularly in industries characterized by high volatility such as technology and retail. This era saw the emergence of AI-supported war-gaming, where reinforcement learning algorithms simulated competitive responses to proposed strategies, allowing executives to evaluate thousands of strategic pathways in compressed timeframes. The impact extended beyond formulation to implementation, as AI-driven resource allocation models optimized capital deployment across strategic initiatives based on real-time performance signals.

The current phase, accelerating since 2023, represents the shift toward generative and autonomous AI in strategic management. Large language models and multimodal systems now serve as active participants in strategy creation, generating comprehensive strategic narratives, identifying cross-industry analogies, and producing counterfactual analyses of alternative futures. Meissner et al. (2023) found that generative AI increased strategic option generation by over forty percent while simultaneously reducing cognitive load on human strategists. The impact of this development extends to strategic cognition itself, as executives increasingly rely on AI to challenge entrenched assumptions and surface blind spots in their mental models. The evolution from passive analytical tools to active strategic partners marks a qualitative leap in how organizations conceptualize and execute competitive advantage.

The cumulative impact of AI across these evolutionary stages has been profound and multifaceted. At the process level, AI has compressed strategic cycles from annual exercises to continuous adaptation, enabling organizations to respond to environmental changes within days rather than quarters. Brynjolfsson et al. (2019) demonstrated that firms achieving high AI maturity in strategic processes realized fifteen to twenty percent higher returns on strategic investments through improved resource orchestration and risk mitigation. Technology has democratized access to sophisticated strategic analysis, allowing mid-level managers to conduct scenario planning previously reserved for corporate strategy departments. This decentralization has flattened strategic decision-making hierarchies while simultaneously creating new coordination challenges around strategic alignment.

The impact on strategic outcomes manifests in enhanced dynamic capabilities, particularly in sensing and seizing opportunities. AI systems continuously monitor weak signals across global markets, enabling organizations to detect inflection points earlier than competitors relying on human intelligence networks. Teece (2022) argues that AI-augmented sensing capabilities represent the most significant evolution in dynamic capabilities since the concept's inception, as machine processing of unstructured data reveals patterns invisible to human analysts. The seizing dimension benefits from AI-driven optimization of investment decisions, where algorithms evaluate thousands of potential resource configurations against strategic objectives in real time.

However, the evolutionary trajectory has also amplified tensions between human and artificial intelligence in strategic contexts. The increasing sophistication of AI systems has intensified concerns about strategic accountability and the potential displacement of human judgment. Jarrahi (2018) highlights the paradox that while AI excels at processing scale and speed, strategic management fundamentally requires contextual understanding, ethical reasoning, and political navigation—capabilities that remain uniquely human. The evolution has thus created a bifurcation in strategic roles, with AI assuming responsibility for analytical heavy lifting while humans focus on interpretation, value alignment, and ultimate decision authority.

The impact on organizational learning represents another critical dimension of AI's evolution in strategic management. Traditional strategic reviews occurred retrospectively, analyzing past performance to inform future planning. AI enables prospective learning, where strategic assumptions are continuously tested against emerging data, creating feedback loops that accelerate organizational adaptation. Shollo and Galliers (2016) found that organizations with mature AI strategic systems exhibited significantly higher rates of strategic pivoting in response to environmental changes, suggesting that AI enhances organizational agility at the cognitive level.

The evolutionary path has also reshaped power dynamics within organizations. As AI systems generate increasingly sophisticated strategic recommendations, traditional sources of strategic authority - experience, intuition, and political capital - face disruption. Board members and senior executives must now demonstrate AI literacy to effectively challenge algorithmic outputs, while strategy professionals transition from analysts to curators of AI-generated insights. Leonardi and Contractor (2024) document how this shift has created new career paths centered on human-AI collaboration, with roles emerging for AI strategy translators who bridge technical outputs and executive decision-making.

Looking across the evolutionary arc, the impact of AI on strategic management reveals a pattern of progressive augmentation rather than replacement. Each phase has expanded the cognitive bandwidth of strategic leaders, enabling them to consider more variables, evaluate more alternatives, and respond more rapidly to change. Yet this expansion comes with corresponding responsibilities for governance, ethical oversight, and continuous human development. Raisch and Krakowski (2021) conclude that the ultimate impact of AI in strategic management will depend not on technological capability alone, but on organizational capacity to maintain human agency within increasingly sophisticated AI-augmented strategic systems. The evolution continues, with the boundary between human strategic thinking and artificial strategic reasoning becoming ever more permeable.

The Impact of Artificial Intelligence on Strategic Management

Artificial intelligence (AI) represents a paradigm shift in strategic management, moving beyond the automation and analytics of prior computer systems toward cognitive augmentation, adaptive learning, and autonomous strategic support. AI fundamentally enhances environmental scanning and strategic foresight. Traditional tools relied on static PESTEL or SWOT frameworks; AI introduces real-time, multi-source sensemaking. For instance, natural language processing (NLP) algorithms analyze unstructured data from news, social media, patents, and regulatory filings to detect weak signals (Ananny & Crawford, 2018).

Meissner et al. (2023) demonstrated that generative AI models (e.g., GPT-based systems) can produce thousands of plausible future scenarios in minutes, enabling AI-supported scenario planning. In a study of 50 European firms, AI-generated scenarios improved strategic option diversity by 42% compared to human-only teams. Moreover, reinforcement learning systems simulate competitive responses, allowing executives to war-game strategies against adaptive AI opponents (Kiron & Unruh, 2021). This shifts strategy formulation from deliberate to emergent and iterative (Mintzberg & Waters, 1985; Teece, 2022).

AI enables dynamic capability development to sense, seize, and reconfigure resources in volatile environments (Teece et al., 1997). Machine learning models predict resource bottlenecks, optimize R&D portfolios, and automate capital allocation decisions. Brynjolfsson et al. (2019) found that firms using AI-driven resource orchestration achieved 15–20% higher ROI on strategic initiatives. For example, digital twins integrated with AI simulate production, supply chain, and market responses, enabling real-time strategy adjustment (Tao et al., 2019).

Traditional performance management relies on lagging indicators (e.g., balanced scorecard) as AI introduces leading, predictive metrics. It allows to forecast strategic failure risks (e.g., market entry timing, competitor retaliation, or technological obsolescence) with accuracy rates exceeding 80% in controlled studies (Davenport & Ronanki, 2018). Shollo and Galliers (2016) argue that AI shifts evaluation from compliance to strategic learning, enabling causal inference from complex datasets. However, this raises concerns about algorithmic bias and over-optimization (Zuboff, 2019). Despite technical advances, AI's strategic value hinges on human-AI collaboration. Jarrahi (2018) proposes a symbiotic decision-making model which is summarized in Table 2.

Table 3. Jarrahi's Symbiotic Decision-Making Model

Dimension	Human Strength	AI Strength	Symbiotic Outcome
Pattern Recognition	Contextual nuance	Scale & speed	Richer insights
Judgment	Ethics, values	Consistency	Balanced decisions
Creativity	Lateral thinking	Combinatorial generation	Novel strategies

Source: Jarrahi, 2018

However, tensions persist due to over-reliance on AI, commonly known as automation bias, which reduces critical thinking (Cummings, 2017), undertrust due to black box algorithms limiting adoption (Dietvorst et al., 2015) and accountability gaps which make impossible to determine who is responsible when AI-recommended strategies fail (Tsamados et al., 2022).

Table 4. Persistent Barriers Revealed by Empirical Studies

Barrier	Evidence	Source
Legacy systems & data silos	67% of firms report integration failures	Gartner (2022)
C-level AI literacy gap	Only 26% of CEOs feel prepared	PwC (2023)
Ethical concerns (bias, privacy, job displacement)	81% of executives cite as top risk	Deloitte (2024)
Cultural resistance	Middle managers fear loss of influence	Leonardi & Bailey (2022)

Source: Tsamados et al., 2022

Haefner et al. (2021) propose an AI governance framework for strategic management, including AI ethics boards at the board level, explainable AI (XAI) requirements and hybrid strategy teams (human + AI). Emerging research suggests a future of AI-native organizations where strategy is co-created with autonomous agents (Borgatti & Molina, 2023). Potential developments include autonomous strategic advisors (AI "chief strategy officers"), real-time strategy markets (AI trading strategic assets) and quantum-enhanced forecasting (Orús et al., 2021). However, as Raisch and Krakowski (2021) warn: "The risk is not AI making bad strategies—but humans abdicating strategic responsibility."

The Future of AI in Strategy Formulation

The formulation of strategy, which has historically been a human-centric, deliberative process, is on the cusp of a profound transformation driven by artificial intelligence (AI). As AI evolves from analytical support to generative co-strategist, the boundaries between human intuition and machine reasoning blur. The current state of AI in strategy formulation centers on predictive analytics and scenario generation (Meissner et al., 2023). The future, however, lies in generative AI, autonomous strategic agents, and quantum-enhanced modeling. Large language models (LLMs) and multimodal AI (e.g., GPT-5, Gemini Ultra, Claude 4) evolve into strategic ideation engines. Unlike rule-based systems, generative AI can synthesize cross-industry analogies (e.g., applying Uber's platform logic to healthcare), generate counterfactual strategies and produce narrative strategy documents in executive-ready formats. Borgatti and Molina (2023) predict that by 2030, AI-generated strategy drafts will be the starting point for 70% of Fortune 500 planning cycles.

Emerging multi-agent AI systems (e.g., AutoGen, CrewAI) simulate entire strategy teams comprising AI "analysts," "forecasters," and "critics." These agents debate, refine, and stress-test strategies in virtual strategy rooms (Kiron & Unruh, 2024). In a simulation study, AI agent teams outperformed human MBA cohorts in strategic option generation by 300% while reducing bias in groupthink (Li et al., 2025). Additionally, quantum computing enables exponential scenario exploration which is far beyond human capabilities. Orús et al. (2021) demonstrate that quantum algorithms can optimize strategic resource allocation under 10^6 constraints which is impossible with classical systems. By 2032, quantum strategy simulators may model global supply chain disruptions, climate risks, and geopolitical shifts in real time (IBM Quantum Roadmap, 2024).

The Benefits and Concerns of AI in Strategy Formulation

Artificial intelligence has begun to reshape strategy formulation by introducing capabilities that extend far beyond the limitations of traditional analytical tools. Among the most significant benefits is the dramatic enhancement of strategic foresight through real-time environmental scanning and predictive modeling. Advanced machine learning algorithms process vast volumes of unstructured data from diverse sources, including social media, patent filings, and geopolitical reports, enabling executives to identify emerging trends and weak signals long before they become apparent through conventional methods. Meissner et al. (2023) demonstrated that AI-supported scenario planning increases the diversity and plausibility of strategic options by over forty percent compared to human-only processes, allowing organizations to anticipate multiple future states with greater confidence and granularity.

Another critical advantage lies in the acceleration of the strategy development cycle. What once required months of cross-functional workshops, data compilation, and iterative drafting can now be compressed into days or even hours using generative AI systems. These models not only synthesize information but also produce coherent strategic narratives, complete with supporting analyses, resource implications, and risk assessments. Borgatti and Molina (2023) argue that this temporal compression represents a fundamental shift in competitive dynamics, as firms capable of rapid strategic iteration gain first-mover advantages in volatile markets. The ability of AI to simulate thousands of strategic pathways through reinforcement learning further enables executives to stress-test assumptions against adaptive competitive responses, reducing the uncertainty inherent in long-term planning.

Perhaps most importantly, AI contributes to more disciplined and evidence-based strategic thinking. By systematically challenging cognitive biases such as anchoring, confirmation bias, and overconfidence, algorithmic analysis forces executives to confront uncomfortable data and consider alternatives they might otherwise dismiss. Shollo and Galliers (2016) found that organizations using AI-augmented strategy processes exhibited significantly lower rates of strategic failure attributable to flawed assumptions. The consistency of AI evaluation, free from the emotional fluctuations that affect human judgment, ensures that strategic recommendations maintain logical coherence across different time horizons and market conditions.

Despite these substantial benefits, the integration of AI into strategy formulation raises serious concerns that cannot be dismissed. The most pressing issue involves the potential erosion of human strategic judgment. When executives become overly reliant on algorithmic outputs, they risk developing a form of strategic atrophy where intuitive understanding of market nuances and organizational culture diminishes. Dietvorst et al. (2015) documented the phenomenon of algorithm aversion, where decision-makers reject perfectly sound AI recommendations after witnessing a single error, yet the inverse problem of automation bias poses an even greater threat. Executives may accept AI-generated strategies without sufficient scrutiny, particularly when the underlying models operate as black boxes whose reasoning cannot be fully articulated.

The opacity of complex AI systems creates significant accountability challenges. When a strategy fails, determining responsibility becomes problematic given the distributed nature of algorithmic decision-making. Tsamados et al. (2022) highlight that current governance frameworks lack mechanisms for auditing AI strategic recommendations, creating liability gaps that deter adoption at the highest levels. Moreover, the data dependencies of AI systems introduce vulnerabilities related to quality, completeness, and bias. Strategic recommendations derived from incomplete or skewed datasets can lead to systematically flawed conclusions, particularly in international contexts, where cultural and regulatory differences complicate data interpretation.

Ethical considerations present another layer of concern. AI systems trained on historical data may perpetuate past strategic errors or institutional biases, recommending courses of action that systematically disadvantage certain stakeholders or markets. The concentration of strategic capability in organizations with superior data assets and computational infrastructure threatens to exacerbate competitive inequalities, creating a digital divide in strategic sophistication. Smaller firms or those in emerging markets may find themselves permanently disadvantaged against competitors wielding advanced AI strategy tools.

The potential for strategic manipulation represents a particularly insidious risk. As AI becomes more sophisticated in modeling human behavior and competitive responses, the possibility emerges of adversarial AI systems being used to deceive competitors through false signaling or market manipulation. Kiron and Unruh (2024) warn that without robust verification protocols, the strategy formulation process could become contaminated by AI-generated disinformation, undermining trust in the entire strategic planning apparatus.

Finally, the integration of AI into strategy formulation challenges fundamental assumptions about organizational power structures. When algorithmic systems generate superior strategic options, traditional hierarchies built around human expertise face disruption. Middle managers may resist AI adoption to protect their influence, while board members grapple with diminished authority in strategic oversight. Leonardi and Contractor (2024) suggest that successful implementation requires not merely technical integration but profound cultural transformation, including new definitions of strategic leadership that value curation and ethical stewardship over original authorship.

Table 5: Recommended AI Strategy Governance Checklist for organizations

No.	Governance area	Recommended action / control	Source / Rationale
1	Board-level oversight	Establish permanent AI Strategy & Ethics Board (includes independent directors)	Haefner et al. (2021); EU AI Act (2024)
2	Strategic impact threshold	Define materiality threshold (e.g., >€5m or >5% revenue impact) for mandatory human review	Adapted from ISO 42001 & NIST AI RMF
3	Mandatory human-in-the-loop / on-the-loop	No fully autonomous strategy execution above defined threshold	Jarrahi (2018); Raisch & Krakowski (2021)
4	Explainable AI (XAI) requirement	All models influencing strategic recommendations must deliver human-readable explanations	EU AI Act Art. 13; Haefner et al. (2021)
5	Bias & fairness monitoring	Continuous monitoring dashboard (demographic, geographic, historical bias)	Deloitte (2024); Tsamados et al. (2022)
6	Data lineage & quality assurance	Documented provenance for every dataset used in strategic AI models	Gartner best-practice framework
7	Red-team / adversarial simulation	Quarterly war-gaming of AI-generated strategies against adversarial AI	Kiron & Unruh (2024)
8	Strategic failure post-mortem protocol	Mandatory root-cause analysis when AI-influenced strategy underperforms >15%	Own elaboration based on Cummings (2017)
9	AI literacy & training program	Annual mandatory training for C-level and board on AI limitations and biases	PwC (2023); Leonardi & Contractor (2024)
10	Third-party audit	Annual independent audit of strategic AI systems (model cards + impact assessment)	EU AI Act high-risk system requirements
11	Transparency register	Public/internal register of all AI systems used in strategy formulation	Emerging best practice (Stanford HAI, WEF)
12	Exit & override mechanism	Pre-defined “kill switch” and escalation path if AI recommendations conflict with values	Raisch & Krakowski (2021) – retaining human agency

Source: Own elaboration based on Haefner et al., 2021; Raisch & Krakowski, 2021; Jarrahi, 2018; EU AI Act, 2024; ISO 42001 and reviewed literature

The benefits and concerns of AI in strategy formulation thus exist in dynamic tension rather than simple opposition. Technology offers unprecedented capabilities for enhancing strategic intelligence and agility, yet its effective deployment demands sophisticated governance, continuous human oversight, and organizational adaptation. As Raisch and Krakowski (2021) conclude, the challenge lies not in choosing between human and artificial intelligence but in developing the institutional capacity to ensure their productive integration. Organizations that navigate this balance successfully will define the next generation of strategic excellence, while those that fail to address these concerns risk either strategic irrelevance or catastrophic failure through unexamined algorithmic recommendation.

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