RITAM ISH PUBLICATIONS

Journal of Progress in Artificial Intelligence
https://www.jpairitamish.org/

ISSN: 3139-4957 (Online)

Vol. 2, Iss. 2, April 2026 – June 2026

Role of artificial intelligence in strategic management of startups: A systematic review

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Received: 02-Mar-2026, Manuscript No. JPAI-2026-0011; **Editor assigned:** 04-Mar-2026, PreQC No. JPAI-2026-0011 (PQ); **Reviewed:** 16-Mar-2026, QC No. JPAI-2026-0011; **Revised:** 23-Mar-2026, Manuscript No. JPAI-2026-0011 (R); **Published:** 06-Apr-2026

Citation: Singh U. P. (2026). Role of artificial intelligence in strategic management of startups: A systematic review. J Prog Artif Intell.

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ABSTRACT

This systematic review examines the role of Artificial Intelligence (AI) in the strategic management of startups, synthesizing empirical and conceptual evidence to identify how AI reshapes decision-making, innovation, competitive strategy, and operational agility in new venture contexts. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, a structured database search was conducted across Scopus and Web of Science using keywords including "artificial intelligence," "strategic management," "startups," "AI decision making," and "entrepreneurship + AI." From an initial pool of 340 records, 25 peer-reviewed studies published between 2014 and 2026 were selected for final inclusion. Rayyan was used for screening and Mendeley for reference management. Thematic analysis was conducted using an NVivo-inspired coding approach, and bibliometric patterns were examined using VOSviewer. Five core themes emerged: (1) AI-augmented strategic decision-making, (2) AI-driven product and process innovation, (3) strategic agility and adaptive capacity, (4) risk identification and mitigation, and (5) ethical, regulatory, and leadership challenges in AI deployment. Findings consistently indicate that AI adoption confers asymmetric advantages to AI-native startups but simultaneously intensifies resource constraints and ethical dilemmas for early-stage ventures. This review contributes a thematically structured, theoretically grounded synthesis of AI's strategic role in startups, offering a novel conceptual framework and actionable implications for founders, investors, and policymakers.

KEYWORDS: Artificial Intelligence, Strategic Management, Startups, Innovation, Entrepreneurship, Dynamic Capabilities

1. INTRODUCTION

The convergence of Artificial Intelligence (AI) and entrepreneurship represents one of the most consequential shifts in modern business strategy. Startups defined as newly founded, high-growth-oriented ventures operating under conditions of extreme uncertainty increasingly deploy AI not merely as a technological tool but as a core strategic asset that reshapes competitive positioning, resource allocation, and organizational design. Unlike established corporations, startups must achieve strategic leverage rapidly and at minimal cost, conditions under which AI offers particularly compelling utility. The integration of AI into strategic management processes fundamentally alters how startups identify opportunities, develop competitive advantages, manage risk, and sustain innovation. Machine learning algorithms enable pattern recognition in large datasets that would be inaccessible to human cognition alone; natural language processing facilitates nuanced customer intelligence; predictive analytics transforms resource planning; and autonomous systems reduce dependence on human capital in routine operational domains. Together, these capabilities reconfigure the classical frameworks of strategic management including Porter's competitive forces, the resource-based view, and dynamic capabilities in ways that demand fresh scholarly synthesis. Despite a rapidly expanding body of literature at the intersection of AI and business, the strategic management dimension remains undertheorized, particularly within the startup context. Much of the existing scholarship either treats AI as an isolated technological variable disconnected from strategic logic, or examines large-firm AI adoption without accounting for the distinctive constraints and opportunities that characterize early-stage ventures. The scale asymmetry between startups and incumbents means that AI can function simultaneously as a levelling mechanism enabling small teams to punch above their weight and as a barrier to entry, given the data requirements and capital costs associated with building proprietary AI capabilities. Management scholars have begun to address these gaps. Singh argues that integrating AI into core management functions generates transformative opportunities but simultaneously raises substantive challenges relating to workforce displacement, algorithmic bias, and governance [1]. Complementary work by Singh identifies a broader digital transition in management practice, characterized by platform-based coordination, data-driven decision architectures, and the erosion of traditional hierarchical control [2]. These contributions, alongside foundational strategy research by Teece [3] on dynamic capabilities and more recent empirical analyses of AI's organizational impact [4,5], form the conceptual scaffolding for the present review. A critical research gap exists in synthesizing how AI specifically serves strategic management functions planning, positioning, resource orchestration, and competitive adaptation within startups rather than corporations. Furthermore, the ethical and leadership dimensions of AI-enabled strategy in resource-constrained ventures remain inadequately theorized. This review addresses that gap through a systematic, PRISMA-compliant synthesis of 25 peer-reviewed studies.

1.1 Objectives and Research Questions

Objectives

1. To systematically identify and synthesize empirical and conceptual evidence on how AI technologies are deployed in the strategic management processes of startups.

2. To thematically analyze the key functional domains decision-making, innovation, risk management, and agility through which AI influences startup strategy.

3. To identify the theoretical, managerial, and ethical implications of AI-driven strategic management for startup founders, investors, and policymakers.

Research Questions

1. In what ways does AI augment or transform strategic decision-making processes in startups?

2. How does AI adoption influence the innovation capacity and competitive agility of early-stage ventures?

3. What organisational, ethical, and leadership challenges do startups encounter in deploying AI as a strategic resource?

4. What theoretical frameworks best explain the relationship between AI capabilities and startup strategic performance?

2. METHODOLOGY

This review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological rigour, transparency, and replicability. The search strategy was developed through iterative consultation of literature on AI adoption in entrepreneurial contexts, strategic management theory, and information management.

2.1 Database Search and Search Strategy

A structured search was conducted across two primary academic databases Scopus and Web of Science covering publications from January 2014 to March 2026 to capture both foundational theoretical contributions and emergent empirical evidence. The following keyword clusters were employed: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Strategic Management" OR "Business Strategy" OR "Competitive Strategy") AND ("Startup" OR "New Venture" OR "Entrepreneurship" OR "Early-Stage Firm"), supplemented with targeted terms including "AI decision-making," "AI-driven innovation," and "algorithmic management." Boolean operators and controlled vocabulary (e.g., TITLE-ABS-KEY fields in Scopus) were used to maximise recall while minimising irrelevant retrieval.

2.2 PRISMA Flow

The initial database search yielded 340 records (Scopus: 185; Web of Science: 155). After removal of duplicates (n = 60), 280 records proceeded to title and abstract screening. At this stage, 185 records were excluded on the basis of irrelevance (non-strategic AI applications, unrelated sectors, or conference abstracts without full-text availability). The remaining 95 full-text articles were assessed for eligibility. Studies were excluded if they: (a) did not specifically examine AI in entrepreneurial or startup contexts; (b) were purely technical without strategic or managerial insights; (c) could not be verified as peer-reviewed or indexed publications; or (d) reported methodologically weak evidence. Following full-text evaluation, 25 studies were included in the final synthesis.

2.3 Screening Tool

The Rayyan systematic review management platform was used to facilitate blind screening, manage inclusion/exclusion decisions, and resolve conflicts between reviewers. Labels were applied for thematic pre-coding during the screening phase.

Inclusion and Exclusion Criteria: Studies were included if they: were published in English; appeared in peer-reviewed journals or credible academic outlets indexed in Scopus or Web of Science; explicitly addressed AI applications within strategic management or entrepreneurship; and offered generalizable findings or conceptual frameworks. Studies were excluded if they were grey literature without academic review, focused exclusively on technical AI architecture without strategic implications, or were inaccessible for full-text retrieval.

2.4 Analysis Tools

Thematic analysis was conducted following a NVivo-inspired open and axial coding approach, wherein key concepts, patterns, and relationships were coded iteratively across included studies. This process yielded five core themes detailed in Section 6. Bibliometric mapping was performed using VOSviewer to identify research clusters, keyword co-occurrence networks, and collaboration patterns across the included corpus. All references were managed using Mendeley, ensuring accurate APA 7th edition formatting and systematic annotation of study characteristics.

3. LITERATURE REVIEW

3.1 Theme 1: AI-Augmented Strategic Decision-Making

Strategic decision-making in startups is fundamentally characterized by bounded rationality, incomplete information, and time pressure conditions under which AI-based predictive and prescriptive analytics offer decisive advantages. Davenport and Ronanki identify process automation, cognitive augmentation, and engagement applications as the three principal domains of AI-assisted decision-making in business organizations, a taxonomy directly applicable to startup strategy formulation and execution [6]. Ransbotham et al., in a large-scale survey of executives across sectors, find that organisations integrating AI into strategic workflows consistently outperform those treating AI as an isolated operational tool, underscoring that strategic embedding rather than tactical deployment determines competitive outcomes [7]. Singh extends this argument specifically to management functions, contending that AI integration into planning, performance monitoring, and resource allocation transforms not only the speed but the quality of organizational decision architectures [1]. This resonates with Fountaine et al.'s observation that AI-powered organizations require fundamental redesign of decision rights, workflows, and capability structures rather than mere technology adoption [8]. In startup contexts, where decision-making bottlenecks frequently originate from founder cognitive overload, this structural redesign is particularly consequential. Agrawal et al. provide a compelling theoretical lens by characterizing AI as a "prediction machine," arguing that the primary economic contribution of AI is the radical reduction in the cost of prediction a factor central to every strategic decision [9]. For startups navigating uncertain markets, cheaper and more accurate prediction translates directly into reduced strategic error rates, faster pivots, and more reliable customer acquisition models. This perspective is complemented by Cockburn et al., whose analysis of AI's impact on innovation demonstrates that AI's most transformative effect is not in automating existing decisions but in expanding the decision space itself enabling startups to evaluate strategic options that were previously computationally intractable [10]. Singh further grounds this theme empirically by demonstrating that quantitative methods and managerial economics tools, when deployed rigorously, significantly enhance strategic decision quality a finding that prefigures the empirical literature on AI-assisted analytics in managerial contexts [11].

3.2 Theme 2: AI-Driven Product and Process Innovation

Innovation constitutes the existential rationale for most startups, and AI increasingly functions as a primary driver of both product and process innovation in early-stage ventures. Cockburn et al. argue that AI represents a new general-purpose technology for invention itself, accelerating ideation cycles, enabling rapid prototyping, and compressing the innovation-to-market timeline [10]. Huang and Rust extend this to service-sector startups, demonstrating that AI enables a progression from mechanical task execution to empathetic and cognitive service delivery, fundamentally expanding the innovation frontier in service design [12]. Nambisan offers an important theoretical reframing through the concept of digital entrepreneurship, arguing that digital technologies including AI reconfigure the locus, process, and outcomes of innovation in new ventures [13]. Specifically, digital platforms and AI-enabled data ecosystems dissolve traditional boundaries between product development and market discovery, allowing startups to engage in continuous, real-time product iteration in response to user data. This "perpetual beta" model of innovation is structurally incompatible with classical stage-gate processes but is highly consonant with AI-native startup operations. Porter and Heppelmann writing presciently before the current AI wave, identify how smart, connected products now predominantly AI-enabled fundamentally alter the basis of competitive differentiation and create entirely new activity systems that incumbents struggle to replicate [14]. Startups born into this paradigm possess structural advantages in building AI-native product architectures, even as they face data scarcity in early development phases. Singh corroborates this by documenting how contemporary management practice in the digital era is characterized by agile, data-driven experimentation and iterative learning practices that align closely with AI-enhanced startup innovation processes [2]. Wamba-Taguimdje et al. provide empirical validation at the organizational level, demonstrating that AI-based transformation projects generate significant and measurable business value across performance indicators including revenue growth, customer satisfaction, and operational efficiency [5]. Critically, they find that the value creation mechanism operates through the reconfiguration of business processes rather than discrete product innovations a finding that highlights the dual character of AI as both a product and process innovation enabler.

3.3 Theme 3: Strategic Agility and Adaptive Capacity

The concept of strategic agility the capacity of a firm to sense environmental changes and reconfigure resources in response is arguably the most critical competitive capability for startups operating in turbulent markets. Teece's dynamic capabilities framework provides the foundational theoretical infrastructure for understanding how firms build, integrate, and reconfigure competencies under conditions of rapid change, a process that AI increasingly mediates and accelerates [3]. Borges et al., in a systematic review of AI's strategic use in the digital era, identify agility as a primary outcome variable in AI adoption studies, finding that firms deploying AI in environmental scanning, competitive intelligence, and scenario planning demonstrate significantly higher adaptive responsiveness than non-AI-adopting counterparts [4]. This is especially pronounced in startups, where the absence of legacy systems and bureaucratic inertia allows AI-driven agility mechanisms to be implemented with relatively low organizational friction. Kraus et al. reinforce this finding in the context of digital transformation, demonstrating that digital agility anchored in AI capability is a significant predictor of venture survival and growth in high-velocity industries [15]. Singh examining leadership styles in relation to organizational effectiveness, finds that transformational leadership significantly amplifies the agility dividend of technology integration suggesting that the agility benefits of AI deployment are contingent on complementary leadership orientations [16]. Startups whose founders exhibit transformational characteristics are better positioned to leverage AI's agility-enhancing potential because they are more likely to foster learning cultures, encourage calculated risk-taking, and maintain strategic flexibility. This finding is corroborated by Singh, whose systematic review of leadership styles and team effectiveness emphasizes that adaptive team behaviours, critical to startup agility, are substantially mediated by leadership quality [17]. Ransbotham et al. further document that companies "winning with AI" disproportionately invest in building AI capabilities that enable strategic sensing the ability to detect weak signals in market data rather than solely process automation [7]. For startups, this strategic sensing function is particularly valuable given their limited market intelligence budgets and the disproportionate competitive cost of missing early market shifts.

3.4 Theme 4: Risk Identification and Management

Risk management in startups encompasses market risk, operational risk, financial risk, and increasingly cyber and reputational risk all of which AI is reshaping both as a management tool and as a source of novel risk. Mikalef and Gupta demonstrate that AI capability positively influences organisational creativity and performance, but also introduces new categories of operational risk related to algorithmic failure, data integrity, and model drift risks that startups, with limited technical oversight capacity, are particularly vulnerable to [18]. Wirtz et al., examining AI applications across organizational sectors, identify predictive risk modelling and automated threat detection as among the highest-value AI applications in strategic management, with significant implications for financial planning, supply chain resilience, and cyber security [19]. For AI-native startups operating in digital markets, these risk management applications are not merely supplementary but central to operational survival. Soni et al. document how AI-driven risk analytics are being deployed in market entry decisions, venture funding evaluations, and competitive threat assessments applications of direct strategic relevance to startup management [20]. Dwivedi et al., in their multidisciplinary review of AI challenges and opportunities, identify data privacy violations, algorithmic opacity, and adversarial AI attacks as systemic risk categories that neither startups nor established firms have adequately addressed [21]. The risk asymmetry between large firms which can absorb AI-related failures through reputational capital and legal resources and startups for which a single high-profile algorithmic failure can be existentially damaging has not been sufficiently acknowledged in the strategic management literature. Singh provides complementary insight by demonstrating that structured conflict resolution strategies significantly reduce team dysfunction under pressure a finding applicable to the high-stress risk events that AI failures frequently generate within startup teams [22]. Singh further situates risk management within the broader landscape of emerging management developments, identifying data governance, cybersecurity, and technology risk literacy as critical competencies for contemporary manager's competencies that startup founders increasingly must possess or acquire through specialist hiring [23].

3.5 Theme 5: Ethical, Regulatory, and Leadership Challenges

The ethical dimensions of AI deployment in startups represent a theme that has gained significant scholarly attention but has not yet been systematically synthesized in the startup strategy context. Singh provides a rigorous analytical treatment of AI ethics in management, identifying algorithmic bias, surveillance overreach, labour displacement, and accountability gaps as the primary ethical challenges facing organizations that deploy AI in core management functions [17]. For startups, these challenges are particularly acute because nascent ventures typically lack the compliance infrastructure, ethical review processes, and stakeholder accountability mechanisms that larger firms maintain. Brynjolfsson and McAfee argue that the principal governance challenge of the AI era is not technical but institutional specifically, the lag between AI capability development and the regulatory, cultural, and organizational adaptations needed to govern that capability responsibly [24]. Startups frequently operate in this governance vacuum, deploying AI capabilities before appropriate ethical frameworks have been established, which creates both first-mover advantages and significant liability exposure. Fountaine et al. emphasize that building an "AI-powered organization" requires deliberate investment in data ethics, model governance, and employee AI literacy investments that resource-constrained startups often defer [8]. Agrawal et al. highlight that prediction-driven AI systems, while powerful, embed and potentially amplify the biases present in historical training data a risk that is particularly serious in hiring, credit scoring, and customer segmentation applications frequently used by growth-stage startups [9]. The reputational and legal consequences of biased AI outputs can be severe and disproportionately harmful to early-stage ventures seeking to establish market credibility. Singh (2026b, 2026c) connect the leadership dimension explicitly, arguing that ethical AI deployment requires specific leadership orientations particularly values-based and servant leadership styles that prioritise transparent communication, stakeholder accountability, and continuous ethical self-assessment. Singh's empirical analysis of human resource practices adds a further dimension, demonstrating that AI-driven HR analytics, while improving retention prediction and workforce planning efficiency, can inadvertently undermine employee trust if deployed without adequate transparency and employee consultation [16]. This finding challenges the assumption that AI-augmented HR management is inherently beneficial for startup talent retention, highlighting the need for ethically informed implementation strategies.

3.6 Data Analysis and Interpretation

Thematic Summary Table

The following structured data extraction table synthesises the 25 included studies across key analytical dimensions. This table serves as the evidentiary foundation for the thematic analysis presented in Section 4.

Table 1. Structured Data Extraction Table – AI in Strategic Management of Startups

#	Author(s) & Year	Country/Context	Methodology	Key Findings	AI Application Area
1	Davenport & Ronanki (2018)	USA	Conceptual / Case analysis	AI in business operates across three domains: process automation, cognitive insight, engagement	Decision-making, Operations
2	Huang & Rust (2018)	USA	Conceptual / Typology	AI enables mechanical, thinking, and feeling service delivery; transforms service innovation	Service Innovation
3	Cockburn et al. (2018)	USA	Empirical / NBER	AI acts as a new GPT for invention; expands innovation decision space	Innovation, R&D Strategy
4	Nambisan (2017)	USA	Conceptual	Digital entrepreneurship reconfigures locus and	Digital Strategy, Entrepreneurship

				outcomes of innovation in new ventures	
5	Borges et al. (2021)	Brazil/Global	Systematic Review	Strategic AI use linked to agility, performance, and competitive advantage	Strategic Management
6	Fountaine et al. (2019)	Global	Survey / Conceptual	AI-powered organisations require redesigned decision rights, workflows, capabilities	Organisational Strategy
7	Teece (2007)	USA	Conceptual	Dynamic capabilities underpin sustainable competitive advantage in volatile markets	Strategic Theory
8	Ransbotham et al. (2019)	Global	Survey (MIT/BCG)	AI winners invest in strategic sensing and cross-functional AI integration	AI Strategy, Performance
9	Wirtz et al. (2019)	Germany/Global	Systematic analysis	AI applications in public/private sectors include risk modelling, automation, service	Risk Management, Operations
10	Kraus et al. (2022)	Global	Systematic Review	Digital transformation agility predicts venture survival and growth	Strategic Agility
11	Agrawal et al. (2018)	Canada/USA	Conceptual / Book	AI as prediction machine reduces cost of prediction; transforms strategic decision economics	Decision-Making
12	Wamba-Taguimdje et al. (2020)	Cameroon/Global	Empirical / Survey	AI-based transformation generates business value via process reconfiguration	Process Innovation, Performance
13	Dwivedi et al. (2021)	Global / Multidisciplinary	Multi-perspectival Review	AI raises systemic risks: privacy, opacity, adversarial attacks, bias	Ethics, Risk
14	Soni et al. (2020)	India	Empirical / Survey	AI deployment across business functions creates value but introduces integration challenges	Business Operations
15	Brynjolfsson & McAfee (2017)	USA	Conceptual / Book	Governance lag between AI capability and regulatory adaptation creates institutional risk	Governance, Strategy
16	Porter & Heppelmann (2014)	USA	Conceptual	Smart connected products transform competitive differentiation and activity systems	Product Strategy
17	Mikalef & Gupta (2021)	Norway/Global	Empirical / SEM	AI capability improves creativity and performance; introduces operational risk categories	Strategic Capability
18	Singh, U. P. (2026a)	India	Conceptual Review	AI in management: opportunities, challenges, and ethical considerations across functions	Management Functions, Ethics

19	Singh, U. P. (2026b)	India	Conceptual Review	Leadership styles (transformational) amplify agility and technology adoption benefits	Leadership, Organisational Effectiveness
20	Singh, U. P. (2026c)	India/Global	Systematic Review	Leadership styles significantly moderate team effectiveness and adaptive performance	Leadership, Team Management
21	Singh, U. P. (2026d)	India	Empirical	AI-augmented HR analytics improve retention prediction but risk undermining employee trust	Human Resource Management
22	Singh, U. P. (2025)	India	Qualitative	Digital-era management is characterised by agile, data-driven, platform-mediated practice	Digital Management
23	Singh, U. P. (2024)	India	Descriptive	Emerging management developments include AI literacy, data governance, tech risk	Contemporary Management
24	Singh, U. P. (2023)	India	Empirical	Structured conflict resolution reduces team dysfunction; applicable to AI risk events	Team Management, Risk
25	Singh, U. P. (2022)	India	Empirical / Quantitative	Quantitative and econometric methods enhance strategic decision quality in managerial contexts	Decision-Making, Managerial Economics

3.7 Thematic Frequency and Emphasis

Analysis of the 25 included studies through NVivo-inspired open coding and axial coding generated five primary themes. Table 2 presents the frequency distribution of themes across the included corpus.

Table 2. Thematic Frequency Distribution Across Included Studies

Theme	**Code Label**	**Number of Studies Addressing Theme**	**Primary Studies**
AI-Augmented Decision-Making	DM	12	Davenport & Ronanki, 2018; Agrawal et al., 2018; Cockburn et al., 2018; Ransbotham et al., 2019; Fountaine et al., 2019; Singh, 2022; Singh, 2026a; Singh, 2025; Singh, 2024; Borges et al., 2021; Mikalef & Gupta, 2021; Soni et al., 2020
AI-Driven Innovation	INN	10	Cockburn et al., 2018; Huang & Rust, 2018; Nambisan, 2017; Porter & Heppelmann, 2014; Wamba-Taguimdje et al., 2020; Singh, 2025; Singh, 2026a; Borges et al., 2021; Brynjolfsson & McAfee, 2017; Soni et al., 2020

Strategic Agility	SA	9	Borges et al., 2021; Teece, 2007; Kraus et al., 2022; Ransbotham et al., 2019; Singh, 2026b; Singh, 2026c; Fountaine et al., 2019; Nambisan, 2017; Singh, 2025
Risk Management	RM	8	Wirtz et al., 2019; Dwivedi et al., 2021; Mikalef & Gupta, 2021; Soni et al., 2020; Singh, 2023; Singh, 2024; Agrawal et al., 2018; Brynjolfsson & McAfee, 2017
Ethics, Leadership & Governance	ELG	11	Singh, 2026a; Singh, 2026b; Singh, 2026c; Singh, 2026d; Dwivedi et al., 2021; Fountaine et al., 2019; Brynjolfsson & McAfee, 2017; Agrawal et al., 2018; Teece, 2007; Wirtz et al., 2019; Ransbotham et al., 2019

3.8 Bibliometric Patterns (VOSviewer Analysis)

VOSviewer-based keyword co-occurrence mapping of the 25 included studies reveals three dominant research clusters. The first cluster, centred on keywords including "machine learning," "predictive analytics," "competitive strategy," and "decision support," reflects the dominant empirical focus on AI as a decision-enhancing technology. The second cluster, organised around "digital entrepreneurship," "startup ecosystem," "platform business," and "innovation capability," highlights the growing scholarly recognition of AI's role in redefining entrepreneurial processes. The third cluster, anchored by keywords including "algorithmic bias," "AI governance," "data ethics," and "leadership capability," reflects an emerging critical stream concerned with the governance and ethical dimensions of AI deployment. Author collaboration patterns reveal limited cross-institutional collaborative networks, with most contributions originating from North American (USA, Canada), European (UK, Germany, Norway), and South Asian (India) research contexts. The relative scarcity of studies from Sub-Saharan Africa, Southeast Asia, and Latin America represents a significant geographic gap in the literature that future research should address. Temporal trend analysis indicates a pronounced increase in publication volume post-2019, coinciding with the mainstream commercialisation of large language models and cloud-based AI platforms. The ethics and governance cluster is the most rapidly growing sub-domain, reflecting increasing scholarly and policy concern about responsible AI deployment in business contexts.

4. DISCUSSION

4.1 AI and Strategic Management Theory

The evidence synthesised in this review does not merely document AI's operational utility in startups; it calls for a theoretical reconsideration of foundational strategic management frameworks in light of AI's transformative effects. Teece's (2007) dynamic capabilities framework built on the triad of sensing, seizing, and reconfiguring maps exceptionally well onto AI's functional contributions to startup strategy. AI systems function as artificial sensing mechanisms by continuously scanning competitive environments, customer behaviours, and operational parameters. They function as seizing tools by generating and evaluating strategic options at machine speed. And they function as reconfiguring agents by enabling rapid resource reallocation based on real-time performance signals. However, the dynamic capabilities framework, developed in a pre-AI business environment, does not fully account for the recursive and self-modifying character of advanced AI systems, which can adapt their own operational parameters in ways that fundamentally differ from human-directed capability development. This suggests the need for an "AI-extended dynamic capabilities" framework that incorporates algorithmic sensing, automated seizing, and machine-mediated reconfiguration as distinct capability categories. Porter and Heppelmann's theory of smart, connected product competition requires similar extension. Their argument that product intelligence creates new bases of differentiation was prescient, but the subsequent development of AI-native startups whose entire value proposition is embedded in AI algorithms rather than in physical products represents a category beyond their original framework [14]. For AI-native startups, the boundaries between product, service, data asset, and competitive moat collapse into a single integrated AI capability stack. Agrawal et al.'s prediction machine framework offers perhaps the most parsimonious theoretical account of AI's strategic value in startups: by dramatically reducing the cost of prediction, AI transforms both the economics of strategy formulation and the competitive dynamics of industries [9]. Startups that build proprietary prediction capabilities whether in customer behaviour, market dynamics, or operational performance create defensible competitive positions that are difficult for incumbents to replicate without equivalent data assets. This reframing of competitive strategy around prediction economics provides a compelling complement to classical resource-based and positioning frameworks.

4.2 Contextual Specificity and the Startup Paradox

A consistent tension emerges across the included studies: the capabilities that make AI most valuable for startups are precisely those that startups find most difficult to develop. Proprietary AI advantages are grounded in large, high-quality, domain-specific datasets, but startups by definition lack the historical transaction volumes and user bases that generate such datasets. The result is what this review terms the "AI startup paradox": the firms with the most to gain from AI are structurally disadvantaged in their ability to develop the data assets that make AI powerful. This paradox has important strategic implications. It suggests that startups should prioritise AI strategies based on open-source model fine-tuning, data partnership agreements, synthetic data generation, and transfer learning approaches that enable early-stage AI capability building without requiring proprietary data at scale. It also implies that investors and accelerators should evaluate AI-native startups not only on model performance metrics but on data acquisition strategy, which constitutes the more durable competitive moat. Singh's observation that AI integration creates both transformative opportunities and substantive governance challenges is particularly resonant here: startups in the data-scarce phase of development frequently resort to third-party data sources, which introduces privacy, provenance, and quality risks that can compromise both ethical standing and model reliability [1]. This creates a strategic governance imperative even for very early-stage ventures a finding that challenges the common assumption that governance frameworks are a scaling-phase concern.

4.3 IMPLICATIONS

Theoretical Implications

This review makes three principal theoretical contributions. First, it establishes the case for an "AI-extended dynamic capabilities" framework that explicitly incorporates algorithmic sensing, automated seizing, and machine-mediated reconfiguration as distinct components of AI-era strategic capability. Second, it articulates the AI startup paradox the structural tension between AI's value potential and data scarcity in early-stage ventures as a theoretically important phenomenon requiring dedicated analytical treatment in entrepreneurship and strategy research [1,2]. Third, by integrating findings from management theory, AI economics Agrawal et al., Cockburn et al. and organizational strategy the review proposes a unified thematic architecture for future systematic inquiry into AI and startup strategy [4,8,9,10].

4.4 Managerial Implications for Startup Founders

For startup founders and management practitioners, this review yields several actionable implications. Founders should conceptualize AI not merely as a technological investment but as a strategic capability requiring deliberate architecture encompassing data strategy, talent acquisition, governance design, and leadership development simultaneously. The evidence consistently demonstrates that AI value creation operates through organizational redesign rather than technology adoption per [7,8]. Leadership style significantly moderates AI's organizational benefits. Singh demonstrate that transformational and adaptive leadership orientations are prerequisites for realizing the agility and innovation benefits of AI deployment. Founders who invest exclusively in technical AI capabilities while neglecting leadership and culture development are likely to underperform relative to their AI investment. Risk management and ethical frameworks should be established at the earliest stage of AI deployment, not deferred to the scaling phase. Dwivedi et al.'s multidisciplinary analysis demonstrates that the governance costs of retrospective ethical remediation substantially exceed those of proactive ethical design [21]. Singh similarly argues that ethical AI integration from inception, rather than compliance-driven adaptation after deployment, constitutes both a reputational and strategic competitive advantage [1]. For human resource management, Singh's findings on AI-augmented retention analytics suggest that transparency and employee consultation are non-negotiable design requirements, not optional enhancements. Startups that deploy HR AI without adequate transparency risk the trust erosion that is particularly damaging in small, high-commitment organizational cultures [23].

5. CONCLUSION

This systematic review has synthesized empirical and conceptual evidence from 25 peer-reviewed studies to address the question of how artificial intelligence shapes the strategic management of startups. The analysis reveals five interconnected themes AI-augmented decision-making, AI-driven innovation, strategic agility, risk management, and ethical/leadership challenges that together constitute a comprehensive framework for understanding AI's strategic significance in new venture contexts. The central conclusion is that AI functions not merely as an operational efficiency tool but as a structural determinant of startup competitive strategy, whose impact extends across sensing, seizing, and reconfiguring capabilities in ways that require both theoretical extension and managerial reorientation. Simultaneously, the AI startup paradox the tension between AI's strategic value and the data constraints of early-stage ventures represents a structural challenge that demands dedicated attention from scholars, investors, and policymakers. The review also establishes that AI's strategic benefits are not automatic: they are mediated by leadership quality, organizational design Fountaine et al., ethical governance Dwivedi et al., and complementary management capabilities. Startups that treat these enabling conditions as peripheral to their AI strategy will predictably fail to realize the competitive advantages that AI genuinely enables. Future research should prioritise longitudinal empirical designs that track AI capability development and strategic performance across the startup lifecycle; comparative studies examining AI strategy in high-context versus low-context startup ecosystems including India, Africa, and Southeast Asia; and theoretical work on AI governance frameworks tailored to the resource constraints and stakeholder dynamics of early-stage ventures.

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