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Artificial Intelligence Strategic Lifecycle: A Literature Review-Based Framework

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ABSTRACT

Purpose. This systematic literature review examines how firms utilise artificial intelligence (AI) as a strategic rather than purely operational resource and develops an integrative conceptual framework of the AI strategic lifecycle. **Design/methodology/approach.** A PRISMA-guided search identified 147 peer-reviewed articles published between 2020 and 2025 across major scholarly databases, including Elsevier (Scopus), Emerald, Springer, and Wiley. The evidence is synthesised through five dominant theoretical lenses: dynamic capabilities, resource-based view (RBV), knowledge-based view (KBV), technology acceptance model (TAM), and disruptive innovation theory (DIT). **Findings.** Dynamic capabilities and RBV explain how organisations mobilise data, algorithms, and AI-related human capital to build and sustain competitive advantage in sectors such as public administration, energy, human resource management (HRM), and research-intensive industries. KBV highlights the role of absorptive capacity and knowledge-sharing routines in transforming AI outputs into innovation, particularly in user-facing contexts such as healthcare and hospitality. In these sectors, TAM is central, emphasising trust, ease of use, and perceived usefulness as key drivers of adoption. In finance, DIT elucidates competitive disruption and incumbent response strategies triggered by AI-enabled entrants. **Practical implications.** The review provides recommendations for practitioners, including investing in organisational learning and absorptive capacity and ensuring transparency of AI-enabled interfaces to translate AI investments into sustainable performance gains. **Originality/value.** By integrating five theoretical perspectives, the review develops a model of the AI strategic lifecycle, offering both a consolidated foundation for future research and a forward-looking agenda for managers seeking to leverage AI as a strategic asset.

Keywords: artificial intelligence; strategic management; innovation; technology adoption; resource-based view; dynamic capabilities; disruptive innovation; knowledge-based view

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Стратегический жизненный цикл искусственного интеллекта: концептуальная модель на основе систематического обзора литературы

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АННОТАЦИЯ

Цель. В данной статье на основе систематического обзора литературы показано, каким образом компании используют искусственный интеллект (ИИ) не только как операционный, но прежде всего как стратегический ресурс, и разработана модель жизненного цикла ИИ на стратегическом уровне. **Методология/подход.** Поиск научных публикаций, проведенный в соответствии с протоколом PRISMA, позволил выявить 147 рецензируемых статей, опубликованных в период 2020–2025 гг. в ведущих научных базах данных (Elsevier/Scopus, Emerald, Springer, Wiley). Интерпретация результатов выстроена с использованием пяти доминирующих теоретических концепций: теории динамических способностей, ресурсной теории фирмы (resource-based view, RBV), теории знаний (knowledge-based view, KBV), модели принятия технологий (technology acceptance model, TAM) и теории разрушительных инноваций (disruptive innovation theory, DIT). **Результаты.** Теория динамических способностей и RBV объясняют, каким образом организации используют данные, алгоритмы и человеческий капитал в сфере ИИ для создания и поддержания устойчивого конкурентного преимущества в таких отраслях, как государственное управление, энергетика, управление персоналом и наукоемкие отрасли. KBV подчеркивает роль поглощающей способности и практик обмена знаниями для преобразования результатов ИИ в инновации, особенно в ориентированных на пользователя секторах, таких как здравоохранение и гостиничный бизнес. В этих секторах центральное место занимает TAM, в рамках которой доверие, легкость использования и воспринимаемая полезность выступают ключевыми драйверами принятия технологий ИИ. В финансовом секторе теория разрушительных инноваций раскрывает механизмы конкурентного разрушения и стратегии реагирования действующих игроков на появление новых участников, использующих ИИ на стратегическом уровне. **Практические выводы.** Обзор предлагает практические рекомендации, такие как инвестиции в организационное обучение и развитие поглощающей способности, а также обеспечение прозрачности ИИ-интерфейсов, что позволяет преобразовать вложения в ИИ в показатели эффективности. **Оригинальность/ценность.** На основе интеграции пяти теоретических концепций предложена модель стратегического жизненного цикла ИИ, что одновременно создает основу для дальнейших исследований и формирует ориентированную на будущее повестку для менеджеров, стремящихся использовать ИИ как стратегический актив.

Ключевые слова: искусственный интеллект; стратегический менеджмент; инновации; принятие технологий; ресурсная теория фирмы; динамические способности; разрушительные инновации; знаниевая теория фирмы

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Introduction

Artificial Intelligence (AI) has emerged as a transformative force in modern business, prompting companies to integrate AI into their strategic planning and decision-making. In this review, strategy is understood as an organisation's high-level plan aimed at achieving long-term goals and sustaining competitive advantage, in contrast to operational approaches focused on day-to-day efficiency and routine optimisation [1].

Within this context, artificial intelligence broadly encompasses technologies that simulate or augment human cognitive capabilities, including perception, reasoning, learning, decision-making, and creativity [2]. This set includes symbolic AI, machine learning (ML), deep learning, natural language processing (NLP), and generative AI. Symbolic AI systems, such as expert systems, rely on explicit rules and logic, whereas ML algorithms, including deep learning, enable systems to learn from data and enhance their performance over time. NLP enables human-like language understanding and communication, whereas generative AI generates new, creative content from learned patterns [3].

AI provides organisations with a distinctive competitive advantage by significantly enhancing their decision-making capabilities. AI enables firms to predict trends, interpret complex market dynamics, and make informed strategic choices, for example, regarding market entry, resource allocation, and innovation investments [4]. It also reshapes managerial processes by supporting opportunity identification and rapid adaptation to competitive shifts, ultimately altering the strategic perspective of decision-making [5].

Recognising the challenges posed to strategy-level management by the disruptive nature of AI, such as data privacy concerns, this systematic literature review (SLR) aims to consolidate fragmented knowledge, synthesise empirical and theoretical findings, and identify existing gaps to guide future research and managerial practice. The review is intended to support both scholars seeking conceptual clarity and practitioners developing strategies for leveraging AI as a long-term competitive asset.

Methodology

Given the complexity and multidisciplinary nature of AI and strategic management, we chose a systematic literature review (SLR) as the most rigorous method to ensure comprehensive, unbiased coverage and reproducible results. While narrative or critical reviews may provide deeper conceptual interpretations, they often lack systematic procedures, which can lead to bias or selective representation [6]. Scoping reviews, although comprehensive, typically do not provide in-depth synthesis or critical appraisal of findings, which was essential for our objectives. Thus, an SLR approach aligned best with our aims for comprehensiveness, theoretical grounding, and methodological transparency.

We followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to enhance the review's transparency and replicability [7]. PRISMA provided clear protocols for documenting each step of the literature search and selection process, which is crucial for managing the extensive volume of publications across diverse academic fields. *Figure 1* presents the PRISMA flow diagram used in this study, outlining each stage of the selection process.

Our search strategy combined AI-related keywords, such as machine learning, generative AI, and NLP, with strategic management terms, including strategic planning and competitive strategy. The search was conducted across the databases of major publishers: Elsevier (Scopus), Emerald, Springer, and Wiley.

To ensure the quality of the evidence base, we restricted the final sample to peer-reviewed articles published between 2020 and 2025 in journals rated 4*, 4 or 3 according to the Academic Journal Guide (AJG) 2024. The AJG 2024[1] classification was chosen due to its reliability and quality by focusing exclusively on top-tier journals indexed in the highest-quality databases such as Scopus. The overwhelming majority of such journals are indexed in Scopus, ensuring that the core dataset derives from high-quality Scopus-indexed publications.

Certain methodological limitations must be acknowledged. One challenge concerned distinguishing strategic studies from operational ones. We excluded papers whose primary focus concerned routine optimisation rather than strategic transformation. Of the 358 retrieved papers, 203 were excluded as operational in scope and 2 as irrelevant. We classified a study as strategic if its core purpose related to long-term organisational direction, competitive positioning, capability development, or strategic renewal.

Thus, through this methodological process, 153 papers met the inclusion criteria, and 147 were ultimately analysed after full screening.

Figure 1 summarises methodological approaches, and descriptive statistics of the final sample, including publication year distribution, and sectors.

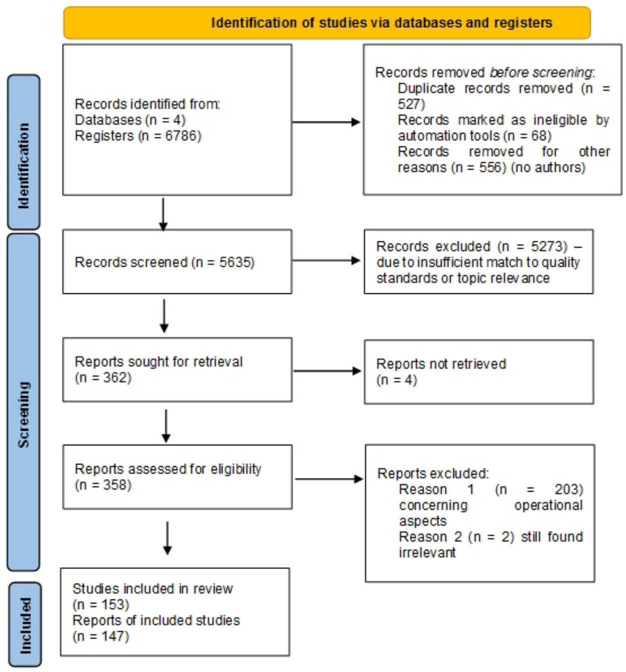

Fig. 1. **Prisma method of data selection**

Source: Compiled by the authors.

Strategic use of AI through theoretical lenses

Analysing theoretical foundations used across the reviewed literature highlights frequently cited theories and provides valuable insights into how these theoretical choices reflect deeper strategic concerns specific to different sectors. Five dominant frameworks emerge: Dynamic Capabilities (DCs), the Resource-Based View (RBV), the Knowledge-Based View (KBV), the Technology Acceptance Model (TAM), and Disruptive Innovation Theory (DIT). Their prominence underscores broader strategic issues, such as resource allocation, capability development and technology acceptance, which organisations grapple with when integrating AI into their strategies (*Fig. 2*). *Figure 2* shows how frequently each theoretical lens appears across major sectors included in the review.

AI literature is broadly divided into several domains. A general perspective explores AI-driven innovation, examining how Dynamic Capabilities (DCs) influence the success of AI adoption across sectors and how firms align their internal AI resources with external market factors to achieve strategic advantage. At the same time, numerous sector-specific studies focus on AI-driven capabilities in such sectors as energy or healthcare, with particular attention to (1) knowledge-management practices that maximise strategic benefits from AI

[1] Academic Journal Guide 2024. Chartered Association of Business Schools. URL: https://charteredabs.org/academic-journal-guide/academic-journal-guide-2024 (accessed on 20.03.2024).

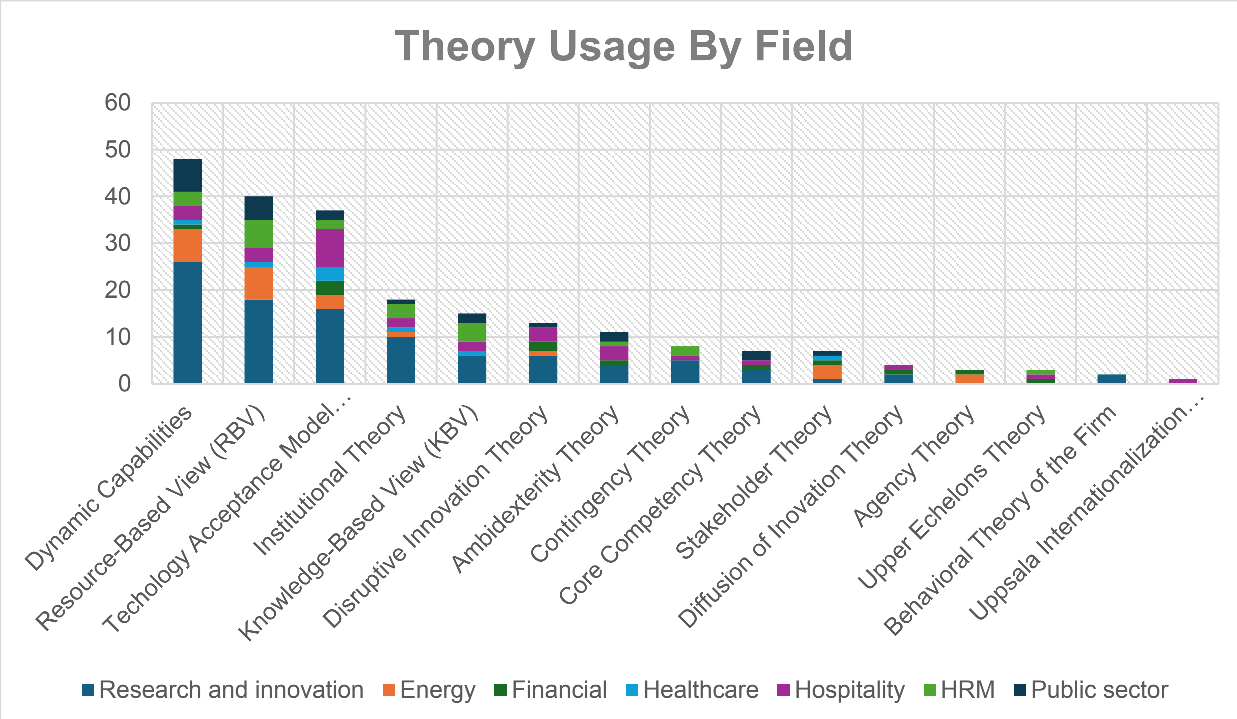

Fig. 2. **Theory usage by field**

Source: Compiled by the authors.

(KBV), (2) TAM-related issues of trust, transparency and perceived usefulness, and (3) strategic responses to potentially disruptive AI technologies (DIT).

Dynamic capabilities and RBV are frequently foundational in sectors like the public sector, human resource management (HRM), energy, and research and innovation. This finding indicates that these sectors perceive AI not only as a technological tool but also as a strategic enabler requiring firms to leverage internal resources, adapt rapidly to environmental changes, and restructure organisational processes. The recurring use of these theories suggests that organisations recognise that AI's strategic value hinges on their ability to transform resources and competencies to maintain competitive advantages continually.

Interestingly, HRM diverges slightly, with the Knowledge-Based View (KBV) replacing dynamic capabilities as the secondary theory. This shift highlights the unique strategic role of human expertise, organisational knowledge, and learning processes that are essential to successfully deploying AI in HR-focused initiatives, where knowledge management significantly influences competitive positioning. Indeed, KBV is primarily linked to the staff's know-how in explaining a company's performance, indicating employees' capacity to use AI meaningfully. Such capability can form the basis of a competitive advantage that is difficult to imitate and therefore plays a central strategic role [5].

Conversely, sectors involving high levels of user interaction and behavioural complexity, such as hospitality, finance, and healthcare, demonstrate a marked preference for the Technology Acceptance Model (TAM). This preference underscores a critical strategic insight: the ultimate success of AI in these contexts depends not merely on organisational readiness or resource availability but fundamentally on user acceptance and interaction. In hospitality and healthcare, specifically, RBV, alongside TAM, reinforces that user acceptance alone is insufficient; firms must also strategically align their internal resources to exploit the benefits of AI technologies fully [2].

Meanwhile, finance frequently employs disruptive innovation theory alongside TAM. This finding highlights a strategic environment that is particularly sensitive to AI's transformative and industry-altering potential, where businesses are increasingly focused on anticipating and navigating disruptions created by new AI-driven financial technologies.

Thus, the theoretical patterns identified in this analysis (*Fig. 2*) do not merely represent academic preferences but provide profound insights into the strategic imperatives and challenges different sectors encounter when integrating AI. *Table 1* summarises the leading theoretical frameworks used across sectors.

Table 1
Leading theoretical frameworks of industry-specific studies

Industry	Leading models
Energy	Dynamic capabilities and RBV
Public sector	Dynamic capabilities and RBV
Research and innovation	Dynamic capabilities and RBV
HRM	RBV and KBV
Financial	TAM
Healthcare	TAM
Hospitality	TAM

Source: Compiled by the authors.

Theoretical approaches of AI in strategy

This section discusses the findings through the lens of five major theoretical frameworks rather than by industry sector. Recent research increasingly demonstrates that AI acts as a cross-sectoral strategic catalyst, reshaping organisational processes, market structures, and sources of competitive advantage [5].

Accordingly, we examine how each theory, Dynamic Capabilities (DCs), the Resource-Based View (RBV), the Knowledge-Based View (KBV), the Technology Acceptance Model (TAM), and Disruptive Innovation Theory (DIT), has been used to explain AI-enabled strategic transformation. To ensure conceptual clarity and methodological transparency, each subsection: (1) outlines the theory's relevance to AI; (2) synthesises its applications across multiple sectors; (3) identifies its theoretical contributions; and (4) highlights limitations, criticisms, or unresolved gaps.

Figure 2 provides an overview of how often each theoretical lens appears across the major sectors reviewed, and *Table 2* synthesises the main findings for each framework.

Dynamic capabilities

Dynamic capabilities theory focuses on an organisation's ability to sense opportunities or threats, seize (mobilise resources for) those opportunities, and transform by reconfiguring competencies in response to changing environments [8, 9]. Within AI contexts, dynamic capabilities provide a mechanism to explain how strategic transformation unfolds through iterative sensing, experimentation, and renewal [10]. Merely acquiring AI technology is insufficient; firms must build supporting capabilities such as data analytics expertise [11], agile governance structures [12], and organisational cultures that encourage experimentation [13] to adapt and innovate with AI.

This finding helps explain the growing divergence between fast-moving firms that scale AI effectively and slower incumbents that struggle despite comparable technological investments. Organisations with strong DCs can reconfigure assets, redesign workflows, and integrate AI-enabled insights into strategic decision-making, thereby achieving sustained renewal [14].

Those with strong dynamic capabilities can realign resources and routines around AI-driven opportunities, achieving sustained strategic renewal [14]. The main criticism by [15] is that the concept can be abstract and difficult to measure, leading to ambiguity in empirical studies. In AI contexts, a major unresolved issue concerns how DCs emerge for technologies that evolve too rapidly to allow stable capability formation. Many AI-related capabilities are identifiable only retrospectively, making proactive capability building difficult [16]. Chowdhury et al. [17] also argue that dynamic capabilities theory risks tautology and may overlap with other frameworks. Thus, scholars increasingly recommend combining DCs with RBV or KBV to capture both resource foundations and the adaptive processes required for AI-driven transformation.

Thus, while valuable for studying organisational adaptation to AI, it should be applied with clear definitions and combined with complementary perspectives (e.g., the resource-based view) to capture AI's strategic impact. Successful AI adoption requires continuous organisational learning and agility. Firms need dynamic capabilities to integrate AI into core processes and adapt as AI and markets evolve [18]. In finance, stronger capabilities enhance the benefits of AI. Song et al. [19] show that the positive effects of AI on financial decision efficiency are conditional on high levels of learning-based capabilities. In manufacturing and services, the lens explains

AI-driven reinvention (e.g., servitisation), with absorptive capacity moderating the impact of AI on innovation [20]. In the public sector, organisations must reconfigure their competencies to harness AI in response to shifting policy demands. In healthcare, individual capabilities have enabled AI-based innovation; Abadie et al. 2023 [21] combine dynamic capabilities with innovation diffusion models to explain AI adoption in hospital operations. Across sectors, the theory emphasises that high strategic agility and learning capacity are crucial for deploying AI successfully to achieve a competitive advantage.

Overall, the DC perspective highlights that AI's strategic value emerges not from the technology itself but from an organisation's ability to learn, integrate, and reconfigure in response to AI-enabled opportunities.

Resource-based view (RBV)

The Resource-based view (RBV) posits that a firm's competitive advantage stems from unique resources and capabilities that are valuable, rare, inimitable, and well-organised (VRIO criteria). RBV explains why some firms gain lasting AI-enabled advantages while others do not [22]. Applied to AI, RBV frames data, algorithms, and human expertise as strategic assets that can generate sustained advantage if they meet VRIO conditions. It highlights that AI strategy should go beyond short-term gains to developing in-house assets, such as proprietary algorithms or data pipelines, that meet VRIO conditions [23]. This perspective clarifies the emerging performance gaps between firms that treat data as a core asset and those that do not.

In the AI era, RBV is used to analyse how AI-related resources (e.g., proprietary data, specialised algorithms, and human AI expertise) drive performance. When these resources are difficult to imitate, deeply embedded in organisational routines, and protected from competitors, they yield durable advantages. If effectively developed and protected, AI becomes a resource that enables value creation, which competitors cannot easily replicate. Empirical work applies RBV to diverse sectors. Ardito et al. [24] model "AI capability" in e-commerce as a strategic resource of technical skills and management practices, thereby boosting performance through innovation and decision-making. In public services, RBV emphasises internal capacity and knowledge assets; unique data and expertise can improve service delivery [25]. Across finance, healthcare, and energy, stronger AI infrastructures, data assets, or AI-skilled personnel yield superior outcomes [5, 26]. However, AI's strategic value is not automatic; it depends on acquiring and nurturing resources competitors cannot match [27].

RBV faces criticisms in AI contexts. One is that it is static, assuming enduring advantages, while in fast-moving fields, assets like algorithms are quickly commoditised [28, 29]. Scholars thus integrate RBV with dynamic perspectives, stressing the need to refresh and recombine resources [30]. Another limitation is RBV's inward focus, which overlooks external factors such as regulation [25], industry standards, and inter-organisational data ecosystems [31]. In highly interconnected AI markets, these external elements significantly shape the value of internal AI resources. Despite its gaps, RBV remains a foundational lens. Its limitations have encouraged more integrative frameworks (for instance RBV and DCs or RBV and KBV) that capture both the stock of AI resources and the adaptive processes necessary to leverage them.

Knowledge-based view (KBV)

The knowledge-based view is an extension of the RBV that singles out knowledge (information, know-how, and intellectual capital) as the most critical resource for competitive advantage [32]. KBV is highly pertinent to AI in corporate strategy because AI technologies are fundamentally concerned with knowledge; they gather data, identify patterns, generate insights, and sometimes even create new knowledge (e.g., predictive models or recommendations).

KBV posits that firms that effectively create, integrate, and apply knowledge outperform competitors; AI amplifies these processes by automating insight generation and accelerating organisational learning [33].

Literature across sectors has applied KBV to understand AI-driven transformation. In manufacturing, for example, AI adoption has been linked to a firm's absorptive capacity, a knowledge-centric capability. Qu and Kim [34] demonstrate that introducing AI in Chinese apparel companies enhances open innovation outcomes only when the firm can effectively absorb and utilise external knowledge; AI is viewed as a strategic tool to facilitate knowledge absorption and, consequently, innovation. This finding aligns with KBV's notion that leveraging new knowledge (from AI analytics or external data) is key to innovation. In the energy and finance sectors, firms utilise AI to analyse vast amounts of data (technical or market knowledge), supporting strategic decisions. The value lies in how well the firm's knowledge management processes can incorporate AI outputs [35]. Similarly, in healthcare, AI-enabled systems (such as diagnostic decision support tools) illustrate KBV by amplifying what organisations know and can do [34]. Maltsev and Yudanov [36] discuss AI's role through a knowledge-based lens, arguing that effective AI adoption transforms the firm's knowledge stock and capabilities.

Overall, the KBV positions AI simultaneously as a knowledge source, a knowledge processor, and a knowledge amplifier, explaining why firms with superior knowledge-integration practices benefit more from AI initiatives.

The KBV contributes theoretically by explaining the mechanism of AI-enabled strategic change as one of knowledge creation and distribution. It posits that AI's strategic impact enhances the firm's ability to generate insights (e.g., identifying patterns in large datasets), disseminate knowledge rapidly, and apply it to new products or processes. For instance, an AI-driven analytics platform can convert raw data into knowledge about customer behaviour; KBV helps articulate how that new knowledge becomes a strategic asset [37]. The perspective also sheds light on organisational learning: AI can catalyse continuous learning, enabling firms to accumulate organisational knowledge more quickly than their competitors and thus sustain innovation [38]. Nonetheless, there are some limitations to KBV's application in the AI context. First, KBV traditionally assumes knowledge resides in human actors, whereas AI systems introduce non-human knowledge repositories (models, embeddings, synthetic knowledge). This raises questions about knowledge governance and integration [39]. However, AI systems introduce non-human repositories of knowledge (models, databases), this raises questions about how firms govern and integrate AI-generated knowledge with the human-generated one [39]. Another challenge is distinguishing practical knowledge from noise: AI can produce overwhelming volumes of information, and without proper knowledge management, firms may struggle to translate this into strategic action [40].

Additionally, like RBV, KBV does not inherently account for the social or ethical dimensions of knowledge use. Trust in AI-produced insights, acceptance of algorithmic decisions, and cultural barriers all influence whether knowledge generated by AI becomes strategically useful [41]. Organisations must also manage cultural and tacit knowledge issues [42], encouraging employees to learn from AI insights and share their expertise, which may extend beyond what classic KBV models capture.

Despite these gaps, the KBV remains a powerful lens for understanding AI's role in strategy, especially when combined with dynamic or human-centred considerations to address how knowledge is absorbed and utilised.

Technology acceptance model (TAM)

The technology acceptance model is a well-established framework that explains individuals' adoption of new technologies based on their perceived usefulness (the belief that the technology will enhance job performance) and perceived ease of use (the belief that it will be free of effort) [43]. TAM is highly relevant for AI in strategic contexts because, ultimately, the success of AI initiatives often hinges on whether people, employees, managers, or customers accept and effectively utilise AI systems [44].

Even highly sophisticated AI strategies fail when end users resist or do not trust the system, making TAM central to understanding adoption across sectors.

Thus, numerous studies have employed TAM to investigate AI adoption at the user level across various sectors. For example, researchers have extended TAM to study clinicians' or patients' intentions to use AI-driven systems (such as diagnostic AI tools or chatbots) in healthcare. Lee [13] finds that in UAE hospitals, classical TAM factors must be coupled with organisational and strategic support factors to predict AI adoption, highlighting that management support and training significantly influence the perceived usefulness of AI systems.

In manufacturing, Qu and Kim's [34] study of apparel firms incorporates TAM constructs, demonstrating that the perceived usefulness and ease of use of AI technologies among employees mediate adoption, which in turn drives innovation outcomes. TAM or related models have also been applied in HR management (e.g., to study whether HR staff will trust AI recommendations in recruitment) and public sector services (to gauge citizen acceptance of AI-enabled e-government) [45]. The broad takeaway is that human factors, such as trust, ease of interface, and straightforward utility, consistently play a crucial role in AI adoption, whether the context is a nurse using an AI diagnostic aid or a finance analyst utilising an AI-driven decision support tool [46].

The TAM framework contributes by focusing on the micro-level drivers of AI-enabled transformation, user attitudes and behaviours. It reminds strategists that, beyond acquiring AI technology, organisations must ensure users find the AI system beneficial and user-friendly [47]. This theoretical lens explains aspects of strategic change, such as the speed and extent of AI implementation: if employees readily accept an AI tool due to high perceived usefulness, the firm can more quickly integrate that tool into its processes (realising strategic benefits sooner). TAM thus helps predict implementation success and can guide interventions (e.g., training to improve perceived ease of use, or pilot programmes to demonstrate usefulness). However, TAM has known limitations when applied to complex systems, such as AI. One criticism is that TAM is too simplistic and individualistic, largely ignoring organisational and contextual factors [48]. Indeed, studies often find it necessary to extend TAM with additional variables or frameworks (as with the TAM-TOE integrated model in the manufacturing study or adding organisational support in healthcare). It also overlooks organisational readiness, institutional pressures, and system-level enablers that frequently shape enterprise AI adoption [49]. Another gap is that classic TAM does not explicitly include factors such as trust, transparency, or the pivotal ethical considerations for AI [50]. For example, users might consider an AI system advantageous yet still hesitate to use it if they mistrust its decisions or worry about potential bias [51]. Recent research in healthcare highlights this issue: Meyer et al. (2024) [52] show that recognition of bias in AI systems can undermine trust and acceptance. Such findings illustrate that TAM's original constructs may need augmentation, e.g., incorporating the perceived credibility or fairness of AI, to capture fully why specific AI applications face adoption resistance. In summary, TAM provides a foundational understanding of user adoption, which is relevant for AI strategies. However, managers and scholars must address their blind spots by considering richer psychological and contextual factors (often using TAM alongside theories like UTAUT, trust models, or institution-based views in AI deployment studies).

Disruptive innovation theory (DIT)

Disruptive innovation theory describes how new technologies can initially target overlooked or low-end market segments with a simpler, cheaper product, then improve over time to displace established competitors eventually [53]. In corporate strategy research, DIT has been a popular lens through which to interpret the rise of AI as a potentially disruptive technology [54]. The idea is that AI could enable new entrants or business models that start at the margins but rapidly evolve to challenge incumbents, thereby transforming industry structures [55]. Researchers have applied DIT to AI across several domains. In the marketing sector, for example, Elgheit 2025 [54] positions generative AI as a disruptive innovation for marketing firms. His study qualitatively finds that small marketing agencies leverage generative AI tools to produce content and services at lower cost, targeting niche or underserved clients. This classic disruptive pattern could erode the advantages of large agencies if those incumbents are slow to respond [56]. In healthcare, analysts have debated whether AI is a genuinely disruptive force or more of a sustaining innovation. Shipton and Vitale [57] examine AI in healthcare through the lens of disruptive innovation, comparing it to past technological revolutions. Some argue that current AI applications represent incremental improvements, while others see potential for a paradigm shift in care delivery [58]. This finding reflects a broader cross-sector discussion: in finance, for instance, fintech startups using AI (for robo-advising, algorithmic trading, etc.) might be seen as disruptors for traditional banks [59], and in education, AI tutors could disrupt conventional teaching — but the extent of disruption can be debated [60]. Overall, DIT is used to explain the trajectory of AI impact: whether AI enables new competitors to overturn established firms eventually, and how incumbent organisations strategise in response (either by adopting the technology themselves or by focusing on higher-end value that AI newcomers cannot initially match).

The disruptive innovation perspective provides insight into AI's competitive and evolutionary implications for strategy. It highlights aspects of AI-enabled transformation, such as market entry and displacement. For example, it can explain why small, agile tech companies with AI at their core might capture market share from large firms that are slower to innovate. It also frames strategic transformation as a potential industry-level shift, not just an internal change: if AI is truly disruptive, it can redefine customer expectations and the basis of competition (for instance, automating services that used to require human experts, thus changing cost structures and quality benchmarks) [61]. However, DIT faces several criticisms, many of which are amplified in AI contexts. A key critique is that DIT can be challenging to apply predictively — it is often easier to label a technology 'disruptive' in hindsight than to know in advance [62]. In the context of AI, many innovations touted as 'disruptive' may not entirely displace incumbents but rather get co-opted or remain niche. Critics, such as Siddik et al. (2025) [63], have also argued that the theory's definitions can be fuzzy, and not every major innovation (even if transformative) follows the low-end encroachment pattern. This fact holds for AI; some AI applications are adopted directly by top-tier firms to enhance their existing products (a sustaining innovation pattern rather than a classic disruption from the bottom) [64]. Some researchers caution that AI's current impact in specific sectors is evolutionary, not revolutionary, requiring long-term integration with human expertise rather than wholesale replacement [65]. Another limitation is that DIT does not inherently address the ethical and societal disruptions AI brings (e.g., job displacement, regulatory upheavals), focusing mainly on business competition. Thus, while the disruptive innovation theory provides a provocative lens for considering AI's strategic implications, urging companies to anticipate possible upheavals in their industry, it should be used with caution [66]. It benefits from combining empirical analyses and other theories (such as diffusion of innovation or socio-technical systems theory) to judge which AI developments are genuinely disruptive versus sustaining. In summary, DIT helps explain the transformative, and at times turbulent, market-level changes prompted by AI, but it also faces challenges and critiques when it comes to reliably guiding strategic decisions in the face of emerging AI technologies.

Table 2 summarises the theoretical contributions, sectoral applications, and remaining research gaps across the five frameworks.

Based on the theoretical analysis, we propose conceptualising AI-enabled strategy as a continuous and iterative lifecycle rather than a linear progression (see *Fig. 3*). Each technological cycle begins with foundational Technology Adoption (TAM), focusing on user acceptance of technology and ease of use. Firms then progress by accumulating distinct resources (RBV), which are integrated and amplified through knowledge-sharing practices (KBV). This integrated knowledge facilitates continuous renewal of organisational capabilities (dynamic capabilities). Eventually, these renewed capabilities enable firms to respond proactively to disruptive innovations and reshape market dynamics (DIT). Crucially, the cycle restarts as AI technology evolves [67, 68], reinforcing that sustained strategic advantage requires perpetual engagement in this ongoing loop of adoption, resource accumulation, knowledge integration, capability renewal, and disruption management.

Directions for future research

While the literature on AI as a strategic asset rapidly evolves, several important gaps and opportunities remain for future investigation. These opportunities span theoretical, methodological, and sector-specific domains and reflect the continuing need to understand how AI reshapes organisational strategy in diverse and dynamic environments.

Cross-theoretical integration. Future work should develop integrative theoretical models that combine multiple lenses, such as dynamic capabilities, the resource-based view, the knowledge-based view, and the technology acceptance model, to capture the multi-level nature of AI-enabled strategic transformation. While most current studies apply a single dominant theory, real-world AI implementation cuts across resource accumulation (RBV), capability development (DC), knowledge integration (KBV), and user acceptance (TAM) simultaneously. Developing such multi-theoretical approaches would allow scholars to reconcile strategic, organisational, and behavioural dimensions within unified frameworks, enabling richer explanations of AI adoption, scaling, and performance outcomes.

Sectoral comparisons and underexplored industries. There is a clear need for comparative studies to analyse how strategic AI use varies between public and private organisations, regulated and non-regulated environments, and capital-intensive versus service-oriented sectors. Sectors such as education, agriculture, manufacturing (beyond innovation contexts), and creative industries remain significantly under-represented in the strategic AI literature. Future research should therefore target

Table 2
Summary of findings

Theory	Research question	Finding and Key recommendations	References
Dynamic capabilities	How do firms proactively build dynamic capabilities specific to AI? How do dynamic capabilities influence the success of AI adoption across sectors?	Firms proactively build AI-specific dynamic capabilities through systematic investments in absorptive capacity, continuous organisational learning, and agile processes. Specifically, strategic renewal occurs when firms integrate internal competencies with external AI-driven knowledge, ensuring responsiveness to environmental shifts. Cross-sector empirical evidence shows that robust dynamic capabilities significantly moderate the relationship between AI adoption and organisational performance, enabling firms to capitalise on opportunities and innovate rapidly, especially in technologically turbulent sectors such as finance and healthcare	[18–20]
Resource-Based View	What makes AI-related resources sustainably valuable and difficult to imitate? How do firms align internal AI resources with external market factors for strategic advantage?	AI-related resources achieve sustained strategic value primarily through proprietary characteristics — unique data assets, specialised algorithms, and AI-specific human capital — that are costly to replicate and deeply embedded within organisational processes. Effective strategic alignment of these internal resources with external market and regulatory contexts involves continuous recombination and updating, bridging RBV's inherent static limitations with a dynamic perspective, thereby ensuring an enduring competitive advantage despite the rapid diffusion of AI technologies	[24, 27, 30]
Knowledge-Based View	How do organisations effectively integrate AI-generated knowledge with human expertise? What knowledge management practices maximise strategic benefits from AI?	Effective strategic integration of AI-generated knowledge with human expertise requires advanced knowledge-management practices, emphasising absorptive capacity, explicit-tacit knowledge conversion, and adaptive learning mechanisms. Organisations that adopt these practices successfully leverage AI as a tool for amplifying human cognitive capabilities, facilitating rapid knowledge dissemination and innovative application, thereby creating competitive advantages through accelerated organisational learning and strategic adaptability	[34, 36, 38]
Technology Acceptance Model	What organisational factors significantly enhance user acceptance of AI technologies? How should TAM be adapted to incorporate trust, transparency, and ethical considerations specific to AI?	Organisational factors such as perceived management support, targeted training, and inclusive decision-making processes significantly enhance user acceptance of AI by improving perceived usefulness and ease of use. Nevertheless, adapting TAM to AI contexts necessitates incorporating constructs such as trust, transparency, and ethical considerations — factors empirically demonstrated to profoundly influence adoption decisions, especially within highly regulated and ethically sensitive sectors like healthcare and finance	[13, 47, 51, 52]
Disruptive Innovation Theory	Under what conditions does AI act as a truly disruptive innovation? How should incumbents strategically respond to potentially disruptive AI technologies?	AI serves as a genuinely disruptive innovation primarily when it initially addresses overlooked or underserved market segments with simpler, cost-effective solutions, subsequently challenging the market positions of incumbent firms. Strategic responses by incumbents should thus focus on proactively identifying disruptive threats early, investing in strategic agility to either co-opt or neutralise disruptive potential, and continuously adapting their business models to integrate AI technologies effectively — thereby mitigating the transformative threats inherent in disruptive innovation scenarios	[54, 58, 64, 66]

Source: Compiled by the authors.

these sectors, ideally through interdisciplinary approaches combining strategic management, data science, behavioural sciences, and sector-specific expertise.

Longitudinal and post-adoption studies. Most existing research focuses on the drivers of AI adoption and conceptual potential, rather than the real processes through which AI systems are implemented, scaled, institutionalised, or abandoned. Longitudinal studies can help trace how AI strategies evolve, how organisations manage setbacks or unintended consequences, and what factors contribute to sustained competitive advantage or decline. Such studies should also examine governance failures, ethical misalignments, and unintended outcomes over time, offering empirical parallels to the AI strategic lifecycle proposed in *Fig. 3*.

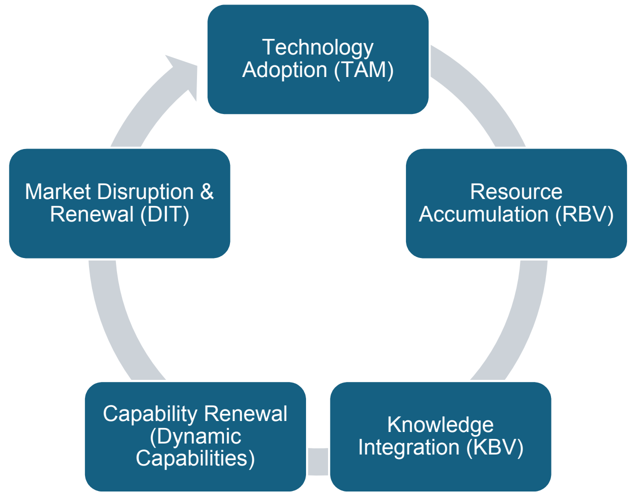

Fig. 3. **The AI strategic lifecycle**

Source: Compiled by the authors.

Conclusion

This systematic literature review highlights the growing strategic importance of AI in contemporary organisational contexts. Drawing from a comprehensive analysis of 147 rigorously selected studies, this review shows that AI has moved far beyond its early perception as an operational efficiency tool. Instead, AI now functions as a central strategic resource that enables sustained competitive advantage, supports continuous innovation, and drives deep organisational transformation.

Our analysis demonstrated that AI integration significantly alters organisational decision-making, enhancing predictive accuracy, strategic agility, and enabling innovative value creation.

The review highlights distinct theoretical orientations aligned with sectoral contexts. Dynamic capabilities and the resource-based view (RBV) are dominant in public administration, human resource management (HRM), energy, research, and innovation. These theories emphasise the importance of internal resource mobilisation, adaptive capacity, and organisational agility necessary for strategically leveraging AI. In HRM specifically, the prominence of the knowledge-based view (KBV) underscores the strategic necessity of managing and leveraging knowledge assets, human capital, and organisational learning to maximise AI's potential.

Conversely, in sectors marked by high behavioural complexity and direct user engagement, such as hospitality, finance, and healthcare, the technology acceptance model (TAM) prevails, emphasising that successful strategic integration of AI fundamentally hinges on user acceptance and interaction. This theoretical focus highlights that strategic considerations must extend beyond internal resource optimisation to include psychological and user-centric factors critical for AI adoption. In finance, the notable application of disruptive innovation theory (DIT) further illustrates sector-specific strategic concerns, particularly how AI-driven innovations can potentially disrupt market structures and challenge traditional incumbents.

Collectively, these theoretical lenses illustrate the multifaceted impact of AI, positioning it simultaneously as a technological enabler, a knowledge asset, a behavioural phenomenon, and a disruptive force. Organisations seeking strategic advantage from AI must navigate complex dynamics beyond mere technical implementation. They must proactively address broader organisational and institutional shifts, human-AI integration challenges, and evolving market conditions. Future research should continue to explore these complexities, with a special focus on cross-sectoral comparisons, longitudinal analyses, and less-explored industries. Moreover, the ethical, regulatory, and governance challenges identified by this review necessitate continued scholarly attention to ensure AI innovations remain transparent, accountable, and aligned with societal values.

In conclusion, this review affirms that strategically implemented AI represents both a theoretical and practical frontier, reshaping individual firm strategies, transforming entire industries, and redefining our broader understanding of technology's role in strategic management.

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