



Closing the knowledge gap: A structured literature review on the mechanisms of AI in enhancing business strategy

A postgraduate dissertation for MBA

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1. INTRODUCTION

1.1 Abstract

Even though artificial intelligence (AI) has become a major priority for many firms' top management teams, turning AI into a clear and effective strategy is still difficult. A central reason is that modern AI systems are not like most other digital technologies: they can learn from data and improve themselves over time, through machine learning. This self-learning capability changes how organizations should plan for, deploy, and control the technology. Yet, strategy research still tries to provide a structured, step-by-step way to help managers decide how to manage these learning systems in alignment with the firm's overall business strategy.

Initially, this project examines such gaps in detail, in every strategy decision lever, and it matches classic and contemporary strategy models, to these levers. Later, it analyzes a newly developed strategy approach grounded in three core features of contemporary AI: First, AI can outperform humans or traditional systems on specific tasks (task superiority). Second, many AI models are difficult to fully interpret, making their outputs feel like a "black box" (black box perception). Third, AI systems can evolve as they learn, meaning their behavior and performance may shift over time (dynamic nature). Built on these characteristics, the newly developed strategy model proposed by Thomas Hutzschenreuter and Tim Lämmermann in their review, constitutes a practical framework that highlights five key questions managers should ask when designing an AI-driven business strategy (Hutzschenreuter and Lämmermann 2025). Here, we walk through each question using several real-world examples, showing how the answers help companies achieve strategic fit, ensuring AI initiatives actually support the firm's goals, capabilities, and competitive positioning rather than becoming isolated tech projects.

1.2. Purpose and Methodology

This dissertation aims to bridge the existing knowledge gap regarding the mechanisms through which Artificial Intelligence (AI) enhances business strategy. While much of the current discourse focuses on the superficial aspects of AI, its capabilities and potential hype, this research interrogates the underlying processes that facilitate effective integration of AI into strategic management. By shifting the focus from the 'what' of AI to the 'how,' this study seeks to provide a comprehensive understanding of AI's role in transforming business strategies and decision-making processes.

To achieve this objective, this study employs a structured literature review methodology guided by the SALSA framework (Search, Appraisal, Synthesis, and Analysis). This approach enables a transparent and systematic organization of existing research while maintaining the conceptual flexibility required to explore the mechanisms through which artificial intelligence enhances business strategy. Peer-reviewed articles published mainly between 2023 and 2026, focusing on the intersection of AI and strategic management are analyzed. AI-assisted tools were used as supplementary support for this analysis, as well as for organizational and linguistic purposes. The intellectual contribution, interpretation of findings, and final validation of the content were performed by the author, as her responsibility, with additional cross-checking supported again by AI applications.

Last, this dissertation will elucidate the various mechanisms through which AI can be effectively leveraged to enhance strategic management practices, thereby contributing to both academic literature and practical applications in the field. Last, except from the positive implications of AI in strategic management, it is essential to acknowledge the challenges and barriers organizations face in adopting these technologies. Thus, issues such as data quality and the need for substantial investments will be discussed, because addressing these challenges will be crucial for organizations aiming to harness the full potential of AI in their strategic endeavors.

2. UNDERSTANDING THE DISTINCTIVE NATURE OF CONTEMPORARY ARTIFICIAL INTELLIGENCE SYSTEMS

A foundational prerequisite for any strategic engagement with artificial intelligence is a clear conceptual grasp of what distinguishes contemporary AI from earlier computational paradigms. At its core, the defining attribute of modern AI lies, not in the execution of pre-specified instructions, but in the capacity for autonomous pattern recognition across vast datasets, a capability broadly captured under the umbrella of machine learning (Berente et al. 2021; Jordan and Mitchell n.d.). Unlike both traditional information systems and the earlier wave of so-called symbolic AI, which relied entirely on decision rules manually extracted from human domain experts (Russell and Norvig 2022), today's systems derive their behavioral logic statistically, identifying correlative structures in data that may exceed the boundaries of human awareness (Tamer Boyacı, Caner Canyakmaz, and Francis de Véricourt 2023). This distinction is not merely technical; it carries profound implications for how organizations conceive of, deploy, and govern these technologies.

One useful way to map the heterogeneity within self-learning systems is along two dimensions: the primary function they serve and the breadth of the task environment for which they are designed (Brynjolfsson and Mitchell 2017; Russell and Norvig 2022). Functionally, a system may be oriented toward generating novel content like text, images, audio, video, or code, or toward estimating outputs for given inputs, supporting classification, forecasting, and decision tasks (Agrawal, Gans, and Goldfarb 2022; Grimes et al. 2023). Orthogonally, a system may be trained for a narrowly specified task or designed to operate across a wide variety of contexts. It has been observed that increasing specificity in the training environment tends to improve fit for a particular application but simultaneously reduces transferability to other domains (Brynjolfsson and Mitchell 2017; Russell and Norvig 2022). This trade-off between specialization and generalizability is a recurring tension in organizational AI adoption, though the literature has yet to provide definitive guidance on how firms should navigate it under varying strategic conditions.

Beyond this classificatory landscape, three inherent characteristics of self-learning technologies have been identified as particularly consequential for strategic management: potential task superiority, the perception of algorithmic opacity, and a dynamically evolving technological frontier (Berente et al. 2021).

Regarding the first characteristic, it has been argued that self-learning systems represent the first class of technologies with the potential to cognitively surpass human performance on certain tasks (Grace et al. 2018). This superiority is, however, conditional rather than universal. It materializes most clearly in contexts that reward rapid processing of large information volumes and logically consistent decision-making (Brynjolfsson and Mitchell 2017). Conversely, significant weaknesses persist. Tasks demanding socioemotional sensitivity, contextual judgment in unprecedented situations, or genuine creative ideation remain domains where human cognition retains a decisive edge (Huang and Rust 2018; McKendrick and Thurai 2022; Wilson and Daugherty 2018). Moreover, although evidence suggests that AI can support certain dimensions of creative work, the management of deep uncertainty still appears to necessitate human imagination and contextual awareness (Brynjolfsson and Mitchell 2017; Jia et al. n.d.). A critical observation here is that much of the discourse on AI superiority risks overgeneralization; the technology's effectiveness is fundamentally task-dependent, and firms that fail to appreciate this conditionality may misallocate resources toward deployment areas where algorithmic strengths are poorly matched to task requirements.

The second characteristic, the black box problem, introduces a distinct set of strategic and organizational challenges. Due to the inherent cognitive limitations of human decision-makers (Tamer Boyacı, Caner Canyakmaz, and Francis de Véricourt 2023), the internal workings of complex machine learning models frequently remain opaque to their users (Barredo Arrieta et al. 2020; Guidotti et al. 2019). This opacity creates what might be described as an adoption paradox: organizations seeking to exploit these systems find themselves unable to fully verify the correctness of the autonomously

learned decision rules on which they depend (Barredo Arrieta et al. 2020). The downstream risks are substantial and well-documented, ranging from erroneous outputs (Doshi-Velez and Kim 2017) and diminished human trust (Glikson and Woolley 2020; Vanneste and Puranam 2024) to more systemic dangers such as security vulnerabilities (Cheng et al. 2022) and the perpetuation of discriminatory biases embedded in training data (Mehrabi et al. 2022). It should be noted, however, that the severity of the black box problem is not uniform; it varies considerably depending on the complexity of the underlying statistical model and the technical literacy of the individuals interacting with the system (Barredo Arrieta et al. 2020). This variability suggests that organizational responses to opacity need to be calibrated rather than standardized.

The third characteristic concerns the rapidly shifting technological landscape in which these systems exist. The field of AI has historically been marked by dramatic paradigm shifts and cyclical periods of enthusiasm and disillusionment (Halevy, Norvig, and Pereira 2009; Russell and Norvig 2022). Contemporary developments, particularly in computer vision, natural language processing, and robotics, continue to reshape the technology frontier at a pace that frequently outstrips organizational capacity for strategic adjustment (Berg, Raj, and Seamans 2023; Brynjolfsson and Mitchell 2017). The sudden emergence and rapid diffusion of generative AI applications serve as a vivid illustration; despite estimates that such technologies could contribute substantially to global economic output (Goldman Sachs 2023), remarkably few organizations had anticipated this particular trajectory of innovation (Edelman and Abraham 2023). This inherent unpredictability raises important questions about whether conventional strategic planning frameworks are adequate for technologies whose capabilities and competitive implications may shift fundamentally within short time horizons.

Taken together, these three characteristics, conditional superiority, pervasive opacity, and technological dynamism, establish that self-learning technologies cannot be treated as incremental extensions of existing digital infrastructure. They demand distinct strategic reasoning, both because they introduce novel sources of competitive value and because they present risks and governance challenges that have no direct precedent in earlier waves of information technology. Any serious attempt to formulate an AI-oriented business strategy must therefore begin with a rigorous understanding of these foundational properties, as failure to do so risks producing strategies that are either naively optimistic about what AI can deliver or insufficiently prepared for the implementation and adaptation challenges it entails (Hutzschenreuter and Lämmermann 2025).

3. KNOWLEDGE GAPS ANALYSIS

3.1. Introduction

Despite the current intensity of corporate interest in AI, the picture remains unbalanced: we have a growing body of conceptual promise, yet far less clarity on how AI actually translates into strategic advantage in practice. The problem is no longer whether firms can access AI, but whether they can convert it into repeatable capabilities, measurable performance, and defensible positioning. Although about 78% of organizations say they have implemented AI in at least one of their business functions, empirical evidence indicates that only around 1% of leaders consider their firms as successfully embedded in AI workflows with consistent substantial business outcomes. (Sira 2025)

This challenge is precisely where many AI initiatives get stuck between technological deployment and operational integration due to knowledge gaps that are simultaneously managerial gaps. Therefore, this section tries to identify these gaps in different strategic decision levers, the mechanisms of which, will be analyzed later in detail.

3.2. Deployment domains: Internal operations & External offerings

The knowledge gaps in this domain derive fundamentally from a mismatch between the pace of technological development and the pace of empirical research. While practitioners have rushed to embed AI across operations and products, scholars have struggled to keep up with systematic evidence about what actually works, where, and under what conditions.

Within internal operations, the gaps originate from the dependence on conceptual rather than empirical inquiry. In other words, conceptual papers far outnumber empirical studies in AI supply chain management, with most existing work discussing deployment principles without measuring actual performance outcomes (Culot, Podrecca, and Nassimbeni 2024). This means that when a firm asks whether AI should be deployed in procurement, logistics, or production, the academic literature offers theoretical possibilities rather than validated guidance. In addition, it has been observed that most operational AI research exists either as conceptual work, early-stage testing, or controlled laboratory experiments that bear little resemblance to the messy realities of organizational implementation (Cannas et al. 2024).

The HR function illustrates a particularly revealing gap: It has been identified that management theories are applied inconsistently to AI-HRM phenomena, creating four distinct transformation pathways—AI-enhanced collaboration, AI-driven workplaces, AI-enabled business models, and AI-powered innovation—whose interconnections remain under-theorized (Gong, Fan, and Bartram 2025). Moreover, the way workers actually interact and emotionally respond to algorithmic technologies across different HR subdomains is poorly understood (Úbeda-García et al. 2025). A systematic review that examined papers published between 2010 to 2024, for AI in operations management, has identified persistent gaps in supply chain management applications, revenue management, and human-AI interaction in operational contexts (Li, Li, and Yao n.d.).

Turning to external offerings, the knowledge gaps derive from a different but equally consequential problem: the assumption that AI's benefits for products and services are self-evident. Commonly cited benefits of AI in product development, rest on opinions or broad surveys rather than rigorous research, meaning that high uncertainties persist about whether and how AI actually enhances market offerings (Cooper 2024). A structured review, based on 190 publications and expert interviews, concludes that AI remains underutilized in concept testing, and that few studies examine integrative AI solutions spanning multiple product development phases. In other words, the literature tends to treat AI as a static tool rather than a force that continuously reshapes market landscapes (Witkowski and Wodecki 2025).

Also, another study based on 159 articles from various fields, revealed that only a small number of firms have effectively used AI for business model creation due to inadequate exploration of AI-enabled design theory and limited understanding of AI's impact on quality function deployment (Naeem, Kohtamäki, and Parida 2025). In addition,

Moreover, there is quantitative evidence that AI-powered growth dominates among larger firms, driving product innovation, and thus, increases industry concentration further. This means that smaller firms attempting to compete, remain critically under-explored (Babina et al. 2024; Oldemeyer, Jede, and Teuteberg 2025).

The combined effect of the aforementioned gaps is that the deployment domain suffers from what might be called an 'evidence vacuum': firms are making consequential decisions about where to place AI bets based on anecdotal success stories rather than systematic empirical understanding of where self-learning technologies genuinely outperform human alternatives.

3.3. Competitive Advantage Levers: Positioning and Defense

This domain concerns how AI creates and sustains competitive advantage, encompassing both the offensive question of competitive positioning and the defensive question of protecting those advantages against imitation. The knowledge gaps here derive from a fundamental theoretical

tension that the field has yet to resolve: If AI, as technological trend towards commoditization, can actually serve as a durable source of competitive advantage.

Back in 2024, the concept of 'situated AI' was introduced, arguing that competitive advantages through AI depend on organizational activities that ground, bound, and recast AI within specific contexts. However, the paper's own commentators identified significant limitations. In addition, it has been argued that the theory is overly intra-firm focused, neglecting boundary spanning activities and ecosystem dynamics that shape how AI generates value in interconnected business environments. This theoretical incompleteness matters because it means scholars cannot yet explain why the same AI capability creates advantage for one firm while failing to do so for another operating in a similar competitive space (Moser, Glaser, and Lindebaum 2024).

Another study compares chess to business. It concludes that the competitive advantage shifts from what AI can substitute to what only humans can complement. In other words, AI doesn't just change who wins. It changes what winning depends on (Krakowski, Luger, and Raisch 2023). Yet, even this influential study acknowledged that its findings from a controlled competitive domain may not translate directly to the complexity of business competition out there. Additionally, many researchers assume that AI-driven business models can create competitive advantages, but in reality, they do so without empirically investigating the mechanisms through which those advantages actually materialize (Jorzik et al. 2024), and this is not a minor oversight. It represents a foundational weakness in the field's ability to advise practitioners.

On the other hand, the defense side, reveals an even more pronounced gap. AI, at its core, is just code and data. Unlike a secret recipe locked in someone's head, code can be copied, algorithms can be reverse-engineered, and data can be collected by anyone willing to invest. So, in theory, any AI advantage a company builds should be easy for competitors to replicate almost for free. That's the paradox, because in reality, some companies do maintain AI-based leads over their rivals for extended periods. Think of how Google's search remains top preference, despite competitors have access to similar machine learning techniques. One explanation to this is that magic isn't in the AI itself but in how a company embeds it into its unique operations, culture, and workflows. For example, a generic recommendation algorithm is copyable, but the way Netflix has woven it into its content decisions, its user interface design, and its specific data collection habits over many years is much harder to imitate. And this process of making a general-purpose technology deeply specific to your organization has been named "situating" (Kemp 2023). The problem here again, is that nobody has actually tested this idea with real data, so we don't know when or why this embedding process works for some firms and fails for others. Another explanation to the same question from the data side, is asking whether having more data creates a protective barrier. The idea behind this is that the more users you have, the more data you collect, and this makes your AI better, capable of attracting more users, and so on (Azoulay, Krieger, and Nagaraj n.d.). Despite, six key assets were found that might serve as protective

barriers, the honest conclusion is that it's simply too early to tell whether any of these will actually hold up over time (Azoulay, Krieger, and Nagaraj n.d.). So, the bottom line is that the debate remains. Until this tension is resolved empirically, the competitive advantage dimension of AI strategy remains built on theoretical ground.

3.4. Profit Model Levers: Revenue Model and Cost Model

Revenue streams and cost structures are two different fundamental levers through which competitive value gets converted into actual profit. The knowledge gaps in this area derive from this notable imbalance where scholars have directed their efforts: considerable research has gone into understanding how AI creates value, while the equally critical question of how firms turn that value into money has been largely overlooked.

On the revenue model side, this gap is arguably the most severe of the ones we study here. The field suffers from fragmentation caused by varied conceptual lenses and units of analysis, while, at the same time, revenue model innovation that is specifically driven by AI, has attracted remarkably little academic scrutiny (Jorzik et al. 2024). The majority of existing work concentrates on value creation rather than value capture, meaning that researchers can articulate how AI enhances products or streamlines operations but cannot systematically explain how firms actually monetize those enhancements. While AI-driven business model innovation has been recognized as a significant outcome of AI deployment, the specific mechanisms through which AI gives rise to entirely new revenue streams remain poorly investigated (Mariani, Machado, and Nambisan 2023)

This problem becomes even more acute in the context of generative AI (AI that creates new content like text, images, music, or code, based on patterns it learned from data). The field currently lacks systematic research into how firms should price and monetize technologies that generate novel content rather than simply process existing information. This gap is especially conspicuous, given the speed at which generative tools have been commercialized (Jorzik et al. 2024). Evidence from multiple case studies suggests that firms find it comparatively straightforward to innovate on how they create value, somewhat harder to innovate on their value proposition, and hardest of all to innovate on how they actually capture value directly confirming the depth of the revenue model gap. Recent research on how generative AI reshapes digital platforms has shown that AI-assisted content creation undermines the exclusivity that previously attached to human-produced work, which means that entirely new approaches to revenue architecture are becoming necessary (Wessel et al. 2025).

On the cost model side, the gaps have a different origin: there is increasingly strong empirical work at individual task level, but this has not yet been translated into strategic frameworks that help firms rethink their overall cost structures. Significant productivity gains from generative AI have been demonstrated in customer support settings, but these results may not transfer across different

production processes, and whether firms will channel AI-driven productivity improvements into augmenting their workforce or replacing it remains a critical but unresolved strategic question (Brynjolfsson, Li, and Raymond 2025). Notably, the finding that AI disproportionately benefits less experienced workers runs counter to prior waves of information technology that tended to favor highly skilled employees, though it is still unclear whether this pattern will hold across different industries and task types (Brynjolfsson, Li, and Raymond 2025)

The concept of a 'jagged technological frontier' has been particularly influential in revealing that AI capabilities are distributed unevenly across tasks. Some tasks see productivity improvements exceeding 40%, while tasks that fall outside the frontier actually suffer quality degradation when AI is applied to them (Dell'Acqua et al. 2023). The way organizations identify where this boundary lies, and what the cost implications are when AI is misallocated to tasks it is ill-suited for, remain critical open questions. Compounding this, organizations currently lack systematic frameworks for optimally dividing work between humans and AI, and the essential process of reallocating human resources when AI takes over certain functions tends to be overlooked entirely (Fügener, Walzner, and Gupta 2026). The net result is a body of literature that can describe AI's impact on individual tasks with growing precision but is not yet able to guide firms on how to restructure their broader cost architecture around effective human-AI configurations.

3.5. Implementations: Trust & Validation and Capabilities & Assets

The implementation dimension asks what firms need to technically apply AI, distinguishing between algorithmic governance—how to handle AI's black box nature—and technological assets required for deployment. The knowledge gaps here derive from what might be called a 'principles-to-practice' chasm: scholars have articulated what responsible, transparent, well-resourced AI implementation should look like, but research on how organizations actually achieve it in practice remains thin.

On the trust and validation side, this chasm is particularly stark. The principles-to-practices gap has been identified as the central challenge in AI governance, with research revealing limited understanding of how governance is actually implemented in organizations, minimal overlap between engineering-oriented AI literature and ethics/regulation literature, and uncertain effectiveness of ethical AI principles when applied in organizational settings (Birkstedt et al. 2023). This finding is reinforced by evidence that responsible AI principles are generally deprioritized or considered ancillary during actual project implementation (Mikalef et al. 2025).

A comprehensive review of ninety articles on algorithmic decision-making in organizations found no integrated theoretical framework, with the tensions between control and autonomy and between transparency and opacity remaining poorly understood (Wang n.d.). Also, a theory of control-accountability alignment among AI developers and users has been proposed, but empirical validation

of this framework remains pending. As a result, fundamental structural problem identified across this literature is that existing governance frameworks treat both context and AI artefact as invariant, while AI systems continuously evolve and adapt, meaning that any static governance approach is inherently mismatched with the technology it seeks to govern.

On the capabilities and assets side, the gaps derive from a fragmented understanding of how organizations assemble and coordinate AI resources. There is currently insufficient knowledge about how organizations should structure AI competencies, particularly at the intersection of tangible resources such as data and infrastructure, human skills including AI talent and intangible resources like organizational learning (Mikalef et al. 2023). Among the most persistent barriers are the inability to integrate systems and data and the difficulty of ensuring quality data for AI training problems that remain unresolved at the organizational level (Papagiannidis et al. 2023). End-user expectations systematically exceed AI capabilities, and the training and education process typically takes months, but research on effective organizational learning processes for AI is lacking (Papagiannidis et al. 2023). A further structural limitation is that research tends to focus exclusively on either SMEs or large firms, restricting understanding of how AI resource requirements differ by organizational size (Ayinaddis 2025). The overarching gap is that while individual implementation challenges are well catalogued, the way organizations orchestrate multiple resource types simultaneously, like coordinating infrastructure, talent, data, partnerships, and change management into a coherent implementation program, remains under-theorized.

3.6. Adaptation Mechanisms: Time horizon and Sensing & Adjusting

Adaptation mechanisms address how firms manage AI's rapidly changing nature, distinguishing between strategic pace, whether to adopt AI radically or incrementally, and sensing mechanisms for detecting when strategy adjustments are needed. The knowledge gaps here derive from the inherent difficulty of studying temporal phenomena in a field that moves faster than the research cycle itself.

On the time horizon side, empirical frameworks are almost entirely absent. Rare empirical evidence on first-mover versus second-mover advantages in AI adoption for micro-businesses has revealed differential advantages for different technology types, but how firm-level contextual factors moderate optimal timing remains unknown (Nafizah, Roper, and Mole 2024). The sequencing of AI adoption within broader strategic frameworks is similarly unaddressed. Research examining AI in strategic decision-making has warned that AI's reliance on past data may create a 'temporal trap', reproducing conventional strategies and reducing novelty, creating an under-researched tension between the speed of AI-augmented strategy creation and its originality (Csaszar, Ketkar, and Kim 2024).

Moreover, distinct AI implementation phases have been identified but there is a significant gap in understanding how quickly firms should move through them, with evidence suggesting that many

firms stuck at the pilot stage without clear conditions for successful acceleration (Haefner et al. 2023). A model of hybrid human-AI problem-solving has been developed but is acknowledged as static while the phenomenon it describes is inherently dynamic, pointing to the need for research on how organizations should pace their transition between different human-AI collaboration modes as AI capabilities evolve (Raisch and Fomina 2025). The compressed timeline between AI being a competitive advantage and becoming a competitive necessity, shorter than any prior technological transition, makes this dimension urgent, and yet it remains paradoxically under-studied.

On the sensing and adjustment side, the gaps are even more pronounced. The most direct conceptual contribution in this area is a framework examining how AI impacts managerial attention allocation for discontinuous change, but even this work emphasizes the critical lack of empirical research to support its propositions (Mundlos 2025). The interaction between AI-aided environmental scanning and managerial cognitive biases, how AI both mitigates and potentially introduces new biases in sensing change signals, remains entirely unexplored empirically. An integrative review bringing together the human-AI collaboration and algorithmic management literatures has identified a critical gap: how organizations sense and detect the moment when AI shifts from being a tool that humans use to a system that manages humans (Hillebrand Luis, Raisch, and Schad 2025).

In a nutshell, cross-industry sensing mechanisms for AI opportunities and threats are virtually unexplored in the academic literature, a significant void given that many consequential AI applications originate in unrelated sectors before diffusing across industries. The adaptation dimension thus suffers from a paradox of its own: the dimension most shaped by temporal urgency is the one where research is least developed, leaving firms to navigate perhaps the most consequential strategic timing decisions of the current era with almost no empirical guidance.

4. CLASSIC AND CONTEMPORARY STRATEGY FRAMEWORKS MAPPED TO AI STRATEGY DECISION LEVERS

Every major strategy framework addresses part of the AI strategy puzzle, but none covers all of it. In this section we examine how the five decision levers proposed (Hutzschenreuter and Lämmermann 2025) for AI strategy (deployment domains, competitive advantage levers, profit model levers, implementation and adaptation mechanisms) map to fourteen classic and contemporary strategy frameworks, showing which slice of the AI strategy challenge each framework illuminates best. The mapping reveals that classic models cluster heavily around deployment domains and competitive advantage levers, while contemporary models skew towards adaptation mechanisms and implementation.

4.1. Classic frameworks

4.1.1. Porter's Five Forces → Deployment domains

Porter's Five Forces framework holds that an industry's profitability is shaped by five structural forces: the threat of new entrants, bargaining power of suppliers, bargaining power of buyers, the threat of substitutes, and rivalry among existing competitors (Porter, 1980). A firm should compete where these forces are most favorable.

This maps most directly to deployment domains. The Five Forces answer the foundational "where" question: which industries, segments, and value chain positions offer attractive terrain for AI deployment. A firm evaluating where to apply AI must first understand the competitive forces shaping each potential deployment domain. For instance, whether AI-powered substitutes threaten existing offerings or whether entry barriers in a target market are high enough to protect AI investments.

4.1.2. Porter's Generic Strategies → Competitive advantage levers

Firms can achieve competitive advantage through one of three strategies: cost leadership (lowest cost in the industry), differentiation (unique offerings commanding a premium), or focus (serving a narrow segment via cost or differentiation). Firms stuck in the middle earn below-average returns (Porter, 1980; Porter, 1985).

This maps squarely to competitive advantage levers, specifically the competitive positioning sub-dimension. The AI strategy framework's choice between "higher customer value" and "lower price" directly mirrors the differentiation-versus-cost-leadership trade-off (Hutzschenreuter and Lämmermann 2025). When a firm uses AI for personalization and enhanced customer experience, it pursues differentiation; when it deploys AI to automate processes and cut costs, it pursues cost leadership. The generic strategies also connect to competitive defense, since a clear positioning choice is the foundation of defensibility.

4.1.3. Porter's Value Chain → Deployment domains

The value chain disaggregates a firm into primary activities (inbound logistics, operations, outbound logistics, marketing and sales, service) and support activities (firm infrastructure, HR, technology development, procurement). Competitive advantage emerges from performing specific activities more efficiently or distinctively than rivals (Porter, 1985).

This maps directly to deployment domains. Indeed, the AI strategy framework explicitly frames its "internal operations" sub-dimension around this concept (Hutzschenreuter and Lämmermann 2025). The value chain provides the operational map for answering "where do we deploy AI?" A firm deciding whether to apply AI in logistics, R&D, or customer service is navigating the value chain to select its AI deployment domains.

4.1.4. Resource-Based View → Implementation

The Resource-Based View (RBV) argues that sustained competitive advantage derives from internal resources and capabilities that are Valuable, Rare, Inimitable, and Non-substitutable (Barney, 1991). A later refinement added "Organization", whether the firm is structured to exploit its resources (Barney, 1995). Earlier foundational work established the broader resource-based perspective (Wernerfelt, 1984).

This maps primarily to Implementation. The RBV focuses attention on the assets a firm needs to execute strategy precisely what the Implementation lever addresses through its "technological assets" sub-dimension (IT assets like data infrastructure and processing power, plus non-IT assets like partnerships, talent, and change management). AI capabilities built on proprietary data, specialized talent, or unique organizational knowledge exhibit classic VRIN properties. The RBV also connects to competitive advantage levers' defense, since inimitable resources are the basis for defending AI enabled positions against rivals.

4.1.5. SWOT Analysis → Strategic Complementarity

SWOT categorizes internal Strengths and Weaknesses alongside external Opportunities and Threats (Puyt, Lie, and Wilderom 2023). SWOT maps most naturally to Strategic Complementarity, the overarching integrating concept. Its fundamental purpose is aligning what a firm can do (strengths and weaknesses) with what the environment demands (opportunities and threats). This mirrors the AI strategy framework's definition of Strategic Complementarity as considering and transferring internal and external firm contexts into each dimension of an AI business strategy. A firm conducting SWOT for AI strategy is asking whether its internal readiness (data assets, talent, culture) aligns with external AI opportunities and threats, precisely the Strategic Complementarity question.

4.1.6. Growth Matrix → Deployment domains

The growth matrix identifies four strategies based on two dimensions: existing versus new products and existing versus new markets. The four resulting strategies are market penetration, market development, product development, and diversification, with risk increasing as a firm moves away from its current products and markets (Ansoff 1965).

This is a near perfect match for deployment domains. The AI strategy framework's deployment domain lever uses strikingly similar 2x2 logic: existing versus new skills and existing versus new offerings. A firm deciding whether to enhance current products with AI features (product development) versus creating entirely new AI-native offerings for new customer segments (diversification) is making precisely the deployment domain decision.

4.1.7. Strategic Archetypes Typology → Adaptation mechanisms

Four organizational archetypes describe how firms adapt to their environments: Defenders (narrow, stable domains, efficiency-focused), Prospectors (constantly seeking new opportunities, innovation-focused), Analyzers (stable core with selective innovation), and Reactors (no consistent strategy—a failing type). The key insight is that strategy, structure, and process must be internally consistent (Miles et al. 1978).

This maps primarily to adaptation mechanisms. The typology is fundamentally about how organizations respond to environmental change, exactly what the adaptation mechanisms lever addresses. Defenders correspond to long-term incremental approaches that prioritize refining existing AI deployments; Prospectors align with short-term radical moves that exploit first-mover advantages in AI; Analyzers blend both time horizons. The typology's emphasis on monitoring the environment also parallels the "handling change" sub-dimension's attention to internal, industry, and industry-independent signals (Hutzschenreuter and Lämmermann 2025). The insistence on internal consistency across strategy, structure, and process additionally connects to Strategic Complementarity (Miles et al. 1978).

4.1.8. Strategy Diamond → Strategic Complementarity

A complete strategy requires five interrelated elements: Arenas (where to be active), Vehicles (how to get there), Differentiators (how to win), Staging (speed and sequence), and Economic Logic (how returns are generated). The central claim is that these elements must fit together as a coherent whole (Hambrick and Fredrickson 2001).

This is the direct ancestor of the AI Business Strategy compass, and it maps to Strategic Complementarity above all else. The AI strategy framework explicitly builds its five levers on the five aforementioned elements. The Strategy Diamond's core argument, that strategy fails when its elements are disconnected, is precisely the Strategic Complementarity principle. Every lever in the AI framework echoes a facet of the diamond.

4.2. Contemporary Frameworks

4.2.1. Blue Ocean Strategy → Deployment domains and Competitive advantage levers

Instead of competing in crowded "red oceans," firms should create "blue oceans"—uncontested market spaces where competition is irrelevant. The cornerstone idea is value innovation: simultaneously pursuing differentiation and low cost, breaking the traditional trade-off (Kim and Mauborgne 2015).

This maps to two levers. First, it aligns with deployment domains because creating new market space is fundamentally about choosing where to compete, specifically, identifying entirely new offerings and skills outside existing competitive boundaries. Second, it connects to competitive advantage levers because value innovation directly addresses competitive positioning (achieving both higher customer value and lower price simultaneously) and competitive defense (making competition irrelevant rather than building barriers against it). Of the two, deployment domains is the more natural fit, since the framework's primary action is market creation.

4.2.2. Dynamic Capabilities Framework → Adaptation mechanisms

Dynamic capabilities describe a firm's ability to integrate, build, and reconfigure competences in rapidly changing environments. Three clusters elaborate this: sensing (identifying opportunities and threats), seizing (mobilizing resources to exploit opportunities), and transforming (reconfiguring the organization's asset base) (Teece 2007).

This maps directly and powerfully to adaptation mechanisms. Adaptation mechanisms lever asks how firms manage AI's changing nature and dynamic capabilities provide the organizational answer. Sensing corresponds to monitoring change signals (internal, industry, and industry-independent). Seizing corresponds to choosing a time horizon and committing resources. Transforming corresponds to organizational reconfiguration as AI matures and paradigms shift. The explicit focus on environments of rapid technological change makes this the most natural theoretical complement to the adaptation mechanisms lever (Teece 2007).

4.2.3. Platform and Ecosystem Strategy → Competitive advantage levers

Platform strategy argues that value creation shifts from linear "pipeline" value chains to multi-sided platforms that facilitate interactions between producers and consumers, generating network effects. Ecosystem strategy extends this to the alignment of interdependent partners delivering complex value propositions (Adner 2017).

This maps most closely to competitive advantage levers, specifically the competitive defense sub-dimension. The AI strategy framework defines "upscaling" as mutually connecting AI systems to create network effects that make imitation complex which is the defining mechanism of platform strategy. Platforms also relate to deployment domains (choosing which multi-sided markets to enter) and profit model levers (platform-based revenue models), but the clearest conceptual link is to the defensive power of network effects in the competitive advantage lever.

4.2.4. Digital Business Strategy → Strategic Complementarity

IT strategy and business strategy have fused into a single "digital business strategy," defined as organizational strategy formulated and executed by leveraging digital resources to create differential

value (Bharadwaj et al. 2013). This fusion is organized around four themes: scope, scale, speed, and sources of value creation.

This maps most naturally to Strategic Complementarity, the principle that AI strategy must be woven into business strategy rather than treated as a separate functional concern. The fusion thesis is the digital era precursor to the AI strategy framework's insistence on cross dimensional consistency. The AI Business Strategy Wheel is explicitly positioned as extending this earlier digital business strategy work to account for AI's distinctive self-learning characteristics. The four themes also touch individual levers, scope relates to deployment domains, speed to adaptation mechanisms, sources of value to competitive advantage levers, but the framework's defining contribution is the integrative logic of Strategic Complementarity.

4.2.5. Business Model Canvas → Profit model levers

The Business Model Canvas is a visual tool with nine building blocks describing how a business creates, delivers, and captures value: Customer Segments, Value Propositions, Channels, Customer Relationships, Revenue Streams, Key Resources, Key Activities, Key Partnerships, and Cost Structure. Its academic foundation traces to earlier conceptual work (Osterwalder, Pigneur, and Tucci 2005).

This maps most directly to profit model levers. The Canvas explicitly includes Revenue Streams and Cost Structure as two of its nine blocks, the same two sub-dimensions that define the profit model lever. When a firm uses the Canvas to design AI-enabled business models, it is specifying how AI drives new revenue (e.g., API-based AI services, data monetization) and reshapes costs (automation vs. augmentation). The Canvas also touches Implementation (Key Resources and Key Activities map to technological assets) and deployment domains (Customer Segments and Value Propositions map to market offerings), but its most distinctive contribution is making the profit logic explicit, the Financial Impact question.

4.2.6. Disruptive Innovation Theory → Adaptation mechanisms

Well managed incumbents fail when they ignore disruptive technologies that initially serve low end or new market segments but eventually overtake mainstream markets. The key insight is that incumbents' rational focus on existing customers blinds them to disruption from below (Christensen 1997).

This maps to adaptation mechanisms, specifically the "handling change" sub-dimension. Disruptive innovation theory explains why firms must monitor industry-independent signals (e.g., AI startups entering from adjacent markets) and how failure to respond leads to displacement. It also connects to the time pacing sub-dimension: incumbents that adopt only long-term incremental approaches to AI risk being disrupted by competitors making short-term radical moves. The warning about the asymmetry of motivation, incumbents' reluctance to cannibalize existing businesses, is a critical adaptation mechanism challenge for AI adoption (Christensen 1997).

4.2.7. Transient Competitive Advantage → Adaptation mechanisms

Sustainable competitive advantage is increasingly rare. Firms must learn to cycle through successive advantages, launching, exploiting, and gracefully disengaging, rather than defending a single position. The lifecycle of a transient advantage runs from launch through ramp-up, exploitation, reconfiguration, and disengagement (Mc Grath 2013).

This maps cleanly to adaptation mechanisms. The thesis that advantages are fleeting directly parallels the adaptation mechanisms lever's concern with AI's rapidly changing nature (Mc Grath 2013). The emphasis on continuous reconfiguration and healthy disengagement mirrors the need to manage shifting time horizons and respond to change signals. In AI strategy, where a model's superiority can evaporate with the next algorithmic breakthrough, the transient advantage perspective is especially pertinent to the adaptation mechanism lever's temporal sequencing challenge.

4.2.8. The AI Factory Framework → Implementation

AI fundamentally transforms a firm's operating architecture by removing traditional constraints on scale, scope, and learning. The concept of the AI factory, a firm's data pipeline, algorithm development, experimentation platform, and software infrastructure, describes the engine of AI-centric competition (Iansiti and Lakhani 2020).

This maps most directly to Implementation. The AI factory concept specifies exactly what technological assets a firm needs to apply AI: data infrastructure, computing resources, algorithmic capabilities, and organizational processes for continuous experimentation. This corresponds precisely to the Implementation lever's IT assets and non-IT assets sub-dimensions (Hutzschenreuter and Lämmermann 2025). The framework also touches deployment domains (AI removes scope constraints, enabling entry into new domains) and profit model levers (AI-driven network effects), but its signature contribution, the operational blueprint for building an AI-native firm, is an Implementation insight.

4.2.9. Good Strategy / Bad Strategy → Strategic Complementarity

Most organizations confuse goals, visions, and buzzwords with actual strategy. Good strategy has a kernel with three elements: a diagnosis of the challenge, a guiding policy for addressing it, and coherent actions that implement the policy. Bad strategy exhibits fluff, failure to face the real problem, mistaking goals for strategy, and poor strategic objectives (Rumelt 2011).

This maps to Strategic Complementarity. The insistence on coherence, that diagnosis, guiding policy, and actions must form a logical chain, mirrors the Strategic Complementarity requirement that all five AI strategy dimensions be mutually reinforcing (Rumelt 2011). The critique of "bad strategy" as disconnected goal-setting is directly relevant to AI strategy, where many firms announce AI ambitions without ensuring consistency across playing fields, business value, financial impact, implementation,

and dynamics. The kernel's demand for honest diagnosis also echoes the Strategic Complementarity principle of aligning strategy with real internal and external conditions.

4.3. What This Mapping Reveals About AI Strategy

First, no single framework covers all five levers, which is precisely why an integrative model was needed (Hutzschenreuter and Lämmermann 2025). The Strategy Diamond comes closest, as the direct inspiration for the AI Business Strategy compass, but even it was not designed for the specific challenges of self-learning technologies (Hambrick and Fredrickson 2001).

Second, the classic frameworks cluster around deployment domains and profit model levers, reflecting strategy's traditional focus on industry positioning and competitive advantage. The contemporary frameworks tilt toward adaptation mechanisms, Implementation, and Strategic Complementarity, reflecting the post-2000 shift toward managing rapid technological change, building organizational capabilities, and integrating digital technology into the fabric of strategy. This tilt matters because AI's most distinctive challenges, algorithmic opacity (Implementation), rapid paradigm shifts like generative AI (adaptation), and the need to fuse AI into business strategy rather than bolt it on (Strategic Complementarity), are precisely where contemporary frameworks have more to say.

Third, profit model is the least populated lever, with only the Business Model Canvas mapping there as a primary (Osterwalder and Pigneur 2010). This suggests that the question of how AI concretely drives profit through new revenue streams, existing revenue enhancement, automation savings, or augmentation gains remains undertheorized relative to the more glamorous questions of where to compete and how to win. For practitioners, this gap signals that detailed profit logic thinking deserves more deliberate attention in AI strategy formulation than most frameworks naturally provide.

The overarching lesson is that strategists building AI strategies should draw on multiple frameworks simultaneously, selecting tools that illuminate each lever. The value chain identifies deployment domains; the generic strategies clarify business value (Porter, 1985); the Business Model Canvas structures financial impact (Osterwalder and Pigneur 2010); the RBV and the AI factory guide implementation (Iansiti and Lakhani 2020); dynamic capabilities and transient advantage manage dynamics (Mc Grath 2013; Teece 2007) and the Strategy Diamond enforces the strategic Complementarity that holds everything together (Hambrick and Fredrickson 2001).

5. AI DRIVEN BUSINESS STRATEGIES

5.1. Defining the Strategic Imperatives for AI Adoption

The argument that artificial intelligence demands its own strategic logic, distinct from conventional digital strategy, stems from a recognition that self-learning technologies operate through fundamentally different mechanisms than prior information systems (Berente et al. 2021). While technologies have long been understood as central to how firms compete, access markets, and generate profit (Porter 1996), earlier frameworks for digital business strategy were designed around the properties of manually programmed systems (Bharadwaj et al. 2013b). It has been contended that these frameworks cannot be straightforwardly extended to accommodate technologies whose behavior emerges from autonomous statistical learning rather than explicit human instruction (Brynjolfsson and Mitchell 2017). Simultaneously, the AI management literature has been found to concentrate heavily on adoption processes and technical readiness, leaving the more fundamental question of strategic integration largely unaddressed (Brynjolfsson and Mitchell 2017; Jöhnk, Weißert, and Wyrski 2021).

To fill this gap, a five-question framework has been advanced, with each question anchored in one of the three distinctive properties of machine learning: conditional task superiority, algorithmic opacity, and technological dynamism (Hutzschenreuter and Lämmermann 2025). The first three questions derive from the superiority characteristic. Firms must determine where AI should be deployed such that its strengths in rapid pattern recognition and large-scale data processing are genuinely exploited (Brynjolfsson and Mitchell 2017). They must then clarify how this deployment translates into competitive differentiation, whether through enhanced customer value, improved operational efficiency, or both (Verganti, Vendraminelli, and Iansiti 2020a). Critically, it has been observed that competitive gains do not automatically yield financial returns, necessitating an explicit articulation of how AI-driven value is converted into revenue and cost advantages (Ransbotham, Khodabandeh, and Fehling 2019).

The fourth question engages with opacity. Because many self-learning systems function as black boxes to their users, successful implementation requires mechanisms for validating algorithmic outputs and securing the complementary assets (infrastructure, talent, organizational readiness) that technical deployment demands (Jingyu and Mengxiang 2021). The fifth question addresses dynamism: given the field's history of sudden paradigm shifts, firms need capabilities for anticipating and responding to technological change before strategic commitments become obsolete (Mahidhar and Davenport 2018).

One might reasonably question, however, whether framing these five dimensions as discrete questions risks obscuring their deep interdependence. Decisions about deployment scope cannot be meaningfully separated from assessments of implementation feasibility or financial viability, and in

practice, strategic reasoning about AI likely involves iterative feedback across all dimensions simultaneously rather than a linear progression through them.

This conceptual structure matters because it elevates AI adoption from a technical initiative to a strategic concern requiring integrated reasoning across competitive, financial, operational, and temporal dimensions. For firms navigating intense pressure to adopt self-learning technologies, such a framework provides a disciplined alternative to both reactive experimentation and uncritical technology enthusiasm, while underscoring that strategic coherence, not mere deployment, determines whether AI investments generate durable value.

5.2. Introducing the AI business strategy compass

An effective AI business strategy, must properly answer all these five aforementioned questions, while taking multiple decisions. Here, we analyze a novel framework, the AI strategy compass, where these questions are mapped to the strategy levers mentioned earlier, when the knowledge gaps were explained, in order to guide firms, address these questions for their context.

5.2.1. Deployment domains: Where Should AI Be Applied?

A fundamental prerequisite for any firm seeking to integrate artificial intelligence into its operations is determining precisely where the technology should be applied. This decision is not merely technical but deeply strategic, as the choice of deployment areas ultimately shapes whether AI can generate meaningful organizational impact or remains an underutilized investment. The challenge lies in matching AI's distinctive computational strengths, its capacity for rapid learning, pattern recognition, and logical inference, with organizational contexts where those strengths can be fully leveraged (Brynjolfsson and Mitchell 2017). When this matching is poorly executed, the resulting performance gains tend to be marginal at best.

The notion that AI deployment must be guided by strategic relevance rather than technological novelty deserves emphasis. It has been argued that effective deployment areas are those that allow self-learning systems to create or enhance competencies that matter for a firm's competitive position (Hutzschenreuter and Lämmermann 2025). This implies that organizations should resist the temptation to adopt AI simply because it is available or fashionable. Instead, the selection of deployment contexts should be driven by a careful assessment of where predictive or generative functionalities can substantively improve task performance. However, it is worth noting that such assessments are inherently difficult in practice, particularly for firms with limited AI experience, which may struggle to accurately evaluate where the technology's strengths align with their operational needs.

One useful distinction concerns whether AI is deployed within internal value chain activities or embedded into external market offerings. Regarding internal functions, production environments, for instance, can benefit from AI-powered robotics that accelerate assembly processes or identify defective materials. Similarly, support functions such as procurement and human resources can be augmented through algorithms that autonomously evaluate suppliers or assess job candidates. These applications illustrate how AI's capacity to process large volumes of information and detect non-obvious patterns can translate into tangible operational improvements.

A pragmatic recommendation that emerges from the literature is that firms should initially prioritize enhancing existing competencies rather than attempting to build entirely new ones from scratch (Davenport and Ronanki 2018). The reasoning is straightforward: organizations possess deeper domain knowledge and richer datasets for activities they already perform, which facilitates more effective algorithm training and reduces implementation risk. Ideally, this enhancement should target business-critical skills, particularly those that differentiate the firm from its competitors. Nevertheless, this conservative starting point should not preclude the longer-term ambition of developing novel capabilities. Firms may also pursue the replication of competitors' most valuable skills through AI or invest in building competencies expected to become strategically important in the future, though such efforts naturally carry greater uncertainty.

Turning to external deployment, the integration of AI features into products and services represents an equally significant strategic playing field (Babina et al. 2024). Existing offerings can be redesigned with intelligent features. For example, embedding AI capabilities into digital products or developing complementary applications and platform services. Such incremental enhancements may constitute relatively accessible entry points for firms beginning their AI journey. More ambitious strategies involve creating entirely new AI-enabled offerings or digitizing previously analogue products. While these initiatives typically demand substantial research and development resources, they can serve as powerful sources of market differentiation and may enable first-mover advantages in emerging product categories (Mahidhar and Davenport 2018).

Critically, however, the assumption that AI-enhanced offerings automatically create customer value should not be taken for granted. It has been observed that customers must genuinely perceive AI features as valuable for such deployments to succeed (Gursoy et al. 2019). Where this perception is absent, AI integration risks destroying rather than creating value. A telling example involves a newspaper chain that deployed generative AI to strengthen its writing capabilities but found that article quality suffered because the tasks fundamentally required human context awareness and creative ideation that the technology could not adequately replicate (Hutzschenreuter and Lämmermann 2025). This case highlights an important limitation: AI's self-learning strengths are not universally applicable, and deployment in areas that primarily demand human cognitive qualities,

such as imagination, contextual judgment, or socioemotional interaction, is likely to yield disappointing results (Huang and Rust 2018).

Finally, it has been suggested that firms should seek deployment inspiration from beyond their own industry boundaries (Boudreau and Lakhani 2009). Cross-industry learning can reveal novel application possibilities that may not be apparent from within a single sector's established practices. This outward orientation seems particularly valuable given the breadth of AI's potential applications, though firms must still evaluate whether externally observed use cases translate meaningfully to their own strategic context. Overall, the identification of appropriate deployment areas emerges as a nuanced exercise requiring both technological understanding and strategic judgment, a combination that many organizations are still developing.

5.2.2. Competitive advantage levers: How Does AI Strengthen Our Market Position?

Beyond selecting where to deploy artificial intelligence, firms must grapple with a more consequential strategic question: how AI adoption translates into a measurable competitive advantage. The deployment of self-learning technologies is not inherently valuable; rather, it's worth is contingent upon whether it meaningfully shifts a firm's position relative to industry rivals. This section examines two interrelated dimensions of this challenge: How AI can strengthen competitive positioning through value and price mechanisms, and how firms can protect any resulting advantages from erosion through imitation.

The competitive logic underpinning AI adoption can be understood through the lens of a firm's targeted value-price ratio within its industry (Porter 1996). At its core, AI offers two broad pathways for improving this ratio: enhancing the value that customers receive, or enabling the firm to operate at lower cost and therefore offer more attractive pricing. These pathways are not mutually exclusive, and firms may pursue combinations of both, though clarity about which dimension is being prioritized appears essential for coherent strategy formulation. It has been argued that unique positionings along either dimension can constitute powerful sources of competitive advantage (Kemp 2023), yet achieving such uniqueness requires deliberate design rather than incidental adoption.

On the value side, self-learning algorithms offer several mechanisms for enriching the customer experience. Personalization has emerged as one of the most widely cited applications, whereby AI systems learn individual customer preferences and habits to deliver tailored recommendations or services (Enholm et al. 2022). Additionally, AI can improve service availability. For instance, through chatbot systems capable of providing uninterrupted customer support without the constraints of human working hours (Adam, Wessel, and Benlian 2021). Further possibilities include the gamification and simplification of demanding customer tasks, making routine or effortful activities more engaging or accessible (Uhm, Kim, and Lee 2023). Each of these mechanisms leverages AI's capacity to process information at scale and respond to patterns in user behavior, thereby creating value that would be difficult or prohibitively expensive to deliver through conventional means alone.

On the price side, AI's contribution operates primarily through cost reduction, which can subsequently be passed on to customers or retained as improved margins. It has been identified that self-learning systems can increase both human and machine productivity, reduce operational expenses, and accelerate organizational decision-making processes (Shrestha and Ben-Menahem 2019). For example, predictive maintenance algorithms that anticipate equipment failures can reduce downtime costs, while AI-assisted planning tools can eliminate redundancies in production workflows. The efficiency gains enabled by such applications may be particularly significant in industries where cost leadership is a primary competitive lever. However, it is important to recognize that these cost advantages are only strategically meaningful if they are substantial enough to alter a firm's relative position, marginal efficiency improvements may not justify the investment and organizational disruption that AI adoption typically entails.

A critical but frequently underexplored dimension of AI-driven competitive advantage concerns its sustainability over time. Even when firms successfully enhance their value proposition or reduce costs through AI, these gains can be rapidly neutralized if competitors replicate the underlying systems. It has been observed that such imitation dynamics are a genuine threat, as demonstrated by instances where leading technology firms have copied AI-enabled features from smaller rivals, thereby eroding what had been distinctive selling points (Hutzschenreuter and Lämmermann 2025). This suggests that creating competitive value through AI is a necessary but insufficient condition for lasting advantage—firms must simultaneously invest in mechanisms to defend their position.

The protection of AI-driven advantages hinges significantly on the safeguarding of training data, since the quality and exclusivity of data fundamentally determine algorithmic performance (Hartmann and Henkel 2020). When competitors gain access to comparable datasets, they can train systems of equivalent or superior capability, rendering the original firm's advantage obsolete. Consequently, identifying which data assets are most strategically critical—particularly those to which a firm has exclusive access—becomes an essential defensive priority. Cybersecurity measures such as anomaly detection systems, network monitoring, and access controls represent practical instruments for protecting these assets, though their effectiveness is never absolute in an evolving threat landscape.

A second defensive strategy involves the mutual interconnection of multiple AI systems within a firm's operations. When algorithms are linked so that they share learning data across functions or platforms, the resulting network effects can substantially increase overall system performance while simultaneously raising the complexity and cost of imitation (Iansiti and Lakhani 2020). This interconnection creates a compounding advantage: each additional data source or algorithmic link strengthens the network as a whole, making it progressively more difficult for competitors to replicate the entire ecosystem rather than isolated components (Gregory et al. 2021). Nevertheless, such integration strategies carry their own risks, including increased system interdependency and the potential for cascading failures if one component underperforms.

In summary, the competitive value of AI is neither automatic nor self-sustaining. Firms must deliberately design their AI initiatives to target specific positioning advantages and simultaneously construct barriers against imitation, recognizing that both dimensions require ongoing strategic attention as markets and technologies evolve.

5.2.3. Profit model levers: How Does AI Drive Financial Returns?

A recurring tension in the discourse on artificial intelligence adoption concerns the gap between the competitive advantages that self-learning technologies can theoretically generate and the actual translation of those advantages into measurable financial outcomes. While there is broad consensus that AI can enhance firm performance, evidence suggests that capturing positive financial returns from AI investments remains a persistent challenge for many organizations (Benbya, Davenport, and Pachidi 2020). This difficulty is underscored by high-profile failures; for instance, it was reported that IBM divested its healthcare AI division after years of substantial investment without achieving commercially viable results (Duffy 2022). Such cases caution against the assumption that technological capability automatically yields profitability. Central to financial success with AI is the question of how firms monetize the value that self-learning systems create. One approach involves strengthening existing income channels — deploying AI features that attract additional customers or justify premium pricing tiers within established product and service portfolios (Verganti, Vendraminelli, and Iansiti 2020b). However, it is equally important to recognize that AI opens possibilities for entirely novel monetization models, such as modular add-on services where customers selectively purchase technology-enhanced features. A noteworthy consideration here is that payment need not be exclusively monetary; customer data can itself function as a form of currency, either by fueling further algorithmic training or by being commercialized through third-party arrangements (Reis et al. 2020). This dual nature of AI-generated revenue, direct and data derived adds complexity to strategic financial planning that firms must carefully navigate. On the cost side, financial gains can emerge through reconfiguring the relationship between human labor and algorithmic capability. It was identified that high levels of automation can reduce organizational dependence on human workers, mitigating costs associated with absenteeism, turnover, and wages (Coombs et al. 2020). Yet this framing risks oversimplification. A more nuanced perspective suggests that augmentation, where AI complements rather than replaces human effort, frequently produces superior outcomes, as both agents can focus on the task dimensions where they hold a comparative advantage (Wilson and Daugherty 2018). The choice between substitution and augmentation is therefore not merely operational but deeply strategic, with significant implications for both cost structure and organizational capability development. It should be noted, however, that the relationship between AI-driven cost reduction and profitability is neither linear nor guaranteed. Gains

in operational efficiency must still be deliberately channeled, whether toward offering more competitive pricing or toward expanding profit margins, and this channeling requires deliberate strategic decision-making rather than passive expectation (Ransbotham, Khodabandeh, and Fehling 2019). Moreover, the broader literature indicates that firms frequently overestimate the revenue potential of AI initiatives while underestimating the sustained investment required for implementation and maintenance (Hutzschenreuter and Lämmermann 2025). This asymmetry between expectation and reality remains one of the most significant risks in AI-oriented business strategy. In sum, the financial dimension of AI strategy demands a dual focus: constructing viable revenue mechanisms that capture the value AI creates, while simultaneously restructuring costs through thoughtful human-machine resource allocation. The evidence suggests that neither dimension alone is sufficient, and that strategic coherence between the two is essential for sustainable profitability.

5.2.4. Implementation: How Do We Make AI Work?

The strategic promise of artificial intelligence is fundamentally constrained by the practical realities of its implementation. Even the most carefully conceived AI strategy risks becoming inconsequential if the underlying self-learning systems cannot be successfully deployed within organizational contexts. Indeed, historical evidence points to alarmingly high failure rates in AI adoption projects, with some estimates placing them above seventy percent (Ångström et al. 2023). This implementation gap raises important questions about what organizational and technical preconditions must be satisfied before AI can deliver on its strategic potential.

The Problem of Algorithmic Opacity

Perhaps the most distinctive implementation challenge posed by self-learning technologies, as opposed to conventional information systems, concerns the opacity of their internal decision-making processes. Due to inherent cognitive limitations, human actors frequently struggle to comprehend how complex algorithms arrive at their outputs (Barredo Arrieta et al. 2020). This lack of transparency creates what can be described as a paradox: organizations seeking to exploit AI's superior pattern recognition capabilities find themselves unable to independently verify whether the system's self-learned decision rules are, in fact, correct (Lebovitz, Levina, and Lifshitz-Assa 2021). The consequences of deploying unvalidated algorithms can be severe and wide-ranging. It was identified that operating opaque systems without adequate oversight mechanisms may lead to incorrect outputs, erosion of user trust, systematic biases including racial or gender discrimination, and even security vulnerabilities (Mehrabi et al. 2022). The case of the American real estate platform Zillow serves as a cautionary illustration: its reliance on a complex and insufficiently validated price-

forecasting algorithm resulted in systematic overvaluations and, ultimately, write-downs amounting to hundreds of millions of dollars (Hutzschenreuter and Lämmermann 2025).

To manage this opacity, organizations can adopt differentiated validation approaches what might be termed doctrines, calibrated to the criticality of the task and the characteristics of the stakeholders involved. In contexts where algorithmic failure carries minimal consequences and no individual is directly affected by the output, a purely performance-oriented stance may suffice, wherein the system is evaluated solely by the quality of its results (Doshi-Velez and Kim 2017). However, when tasks carry high stakes as in medical diagnostics or financial decision-making, a deeper form of expert-level scrutiny becomes necessary, involving manual inspection and control of the algorithm's core decision variables. It is worth noting that such intervention may reduce the system's autonomous learning power, creating a well-documented tension between performance and interpretability (Guidotti et al. 2019). A third approach targets situations where outcomes personally affect non-specialist stakeholders; here, the priority shifts toward generating intuitive, stakeholder-oriented explanations that allow laypeople to understand and assess algorithmic behavior. Critically, these three approaches are not mutually exclusive, and organizations may need to combine them within a single deployment environment depending on the diversity of use cases and user profiles.

Resource Requirements Beyond Technology

Implementation success, however, extends well beyond the resolution of black box challenges. It was recognized that the effective operation of AI systems typically demands a portfolio of technological assets, both IT-related and otherwise, that many organizations may not possess at the outset (Sjödin et al. 2021). On the IT side, requirements commonly include additional processing power, data storage infrastructure, sensor networks, and specialized software for collecting suitable training data (Weber et al. 2023). These can be sourced internally through development efforts or externally through acquisition. For example, by procuring cloud computing services to meet processing and storage demands. The choice between internal development and external acquisition carries strategic implications of its own, particularly regarding organizational capability-building and dependency on third-party providers.

Equally significant, though perhaps less immediately obvious, are the non-IT assets required for implementation. It was found that organizational change management constitutes a critical dimension, as strategists must frequently persuade colleagues, customers, and other stakeholders to accept and engage constructively with new AI-driven processes (Li, Li, Wang & Bennett Thatcher, 2021). Resistance to technological change is a well-documented phenomenon, and underestimating its impact can undermine even technically sound implementations (Enholm et al. 2022). Furthermore, strategic technology partnerships between organizations can serve as a powerful implementation accelerant. In particular, data-pooling arrangements where multiple firms share training data have been identified as a potentially transformative mechanism for producing

algorithms of exceptional quality, as they overcome the data limitations that any single organization might face (Bammens and Hünermund 2021).

Critical Reflection

Despite the comprehensive nature of these implementation considerations, some uncertainties remain. The literature tends to present black box doctrines and asset requirements as discrete, manageable categories, yet in practice, the boundaries between them are likely far more fluid and context-dependent. Moreover, while the importance of non-IT assets such as change management and partnerships is acknowledged, the mechanisms through which these factors interact with technical implementation and how their relative importance varies across industries and organizational maturity levels remain insufficiently explored. Future research would benefit from examining these interdependencies more systematically, particularly through longitudinal studies that track how implementation challenges evolve as organizations gain experience with self-learning technologies.

5.2.5. Adaptation mechanisms: How Do We Adapt to AI's Evolution?

Any strategy built around self-learning technologies must contend with the fact that the AI landscape is characterized by continuous and often unpredictable evolution. The field has historically undergone significant paradigm shifts, and contemporary developments in areas such as computer vision, natural language processing, and robotics continue to reshape the technological terrain at pace (Russell and Norvig 2022). The rapid emergence of generative AI applications exemplifies this volatility, a development that caught most firms and scholars off guard, despite estimates that it could contribute substantially to global economic output. Organizations that fail to anticipate such shifts risk strategic obsolescence, as illustrated by well-known cases of firms like Kodak and Nokia, which misjudged the trajectory of technological disruption in their respective industries (Lucas and Goh 2009; Vuori and Huy 2015).

A foundational strategic decision concerns the temporal framing of AI adoption efforts. It was observed that short-term, radical approaches may enable first-mover advantages or allow firms to close competitive gaps quickly, but they carry heightened risk due to limited room for experimentation and the high costs of rapid deployment (Mahidhar and Davenport 2018). Conversely, incremental long-term strategies afford greater opportunity to refine decisions as new knowledge accumulates, though they may result in missed windows of opportunity (Brock and von Wangenheim 2019). Importantly, the suitability of either approach appears contingent on organizational characteristics: digitally mature firms and start-ups may be better positioned for radical timelines, whereas organizations with established processes and structures may benefit from more measured trajectories.

Beyond temporal planning, the capacity to detect and interpret signals of technological change emerges as a critical strategic capability. It was identified that relevant change signals may originate from three distinct layers: internally, from employees who interact with AI systems and may generate innovative insights; within the industry, from competitors, suppliers, or shifting customer expectations; and externally, from scientific breakthroughs at research institutions, developments on open-source platforms, or regulatory interventions such as the European Union AI Act (Laux, Wachter, and Mittelstadt 2024). This multi-layered monitoring requirement suggests that organizations need structured sensing mechanisms rather than ad hoc environmental scanning.

However, a critical limitation of this framing is that recognizing signals of change and responding to them effectively are distinct competencies. The literature acknowledges the importance of detection but offers less guidance on how firms should evaluate, prioritize, and act upon potentially conflicting signals, particularly under the time pressure and uncertainty that characterize rapidly evolving technological domains.

5.2.6. Strategic complementarity as a precondition for effective AI adoption

It was argued that the individual dimensions of an AI strategy, from deployment choices to financial planning and implementation design, cannot function as isolated decisions but must instead cohere into a logically consistent and mutually reinforcing whole. This principle of strategic fit requires that each decision appropriately reflects the firm's internal capabilities and external competitive context (Porter, 1996). Moreover, it was emphasized that success depends not on the strength of any single strategic component but on the alignment among all of them simultaneously (Hutzschenreuter and Lämmermann 2025). However, the literature offers limited empirical guidance on how firms should operationally assess or measure this alignment in practice.

The diagram below summarizes the aforementioned strategy mechanisms and their complementarity, combined into a strategy compass. The answers to the questions of each mechanism, can guide a firm effectively to proper AI strategy.

The AI Business Strategy Compass

Adaptation Mechanisms:

Time Horizon and
Sensing & Adjusting

What enables us to manage AI's changing nature?

- Which time horizon?
- Which approach to handle change?

Deployment Domains:

Internal Operations & External Offerings

Where do we deploy AI?

- Which value chain functions?
- Which products and services?



Implementations:

Trust & Validation and
Capabilities & Assets

What do we need to technically apply AI?

- Which black box doctrine?
- Which technological assets?

Strategic Complementarity

Profit Model Levers

Profit Model Levers:

Revenue Model and Cost Model
What makes our firm financially successful using AI?

- Which revenue streams?
- Which cost structures?

Competitive Advantage Levers:

Positioning and Defense

What value does AI add to become more competitive?

- Which competitive positioning?
- Which competitive defense?

5.3. AI business strategy compass examples

Real world examples of the aforementioned mechanisms will be analyzed in this section.

5.3.1. Deployment domains -> Internal functions

5.3.1.1. Existing Skills — Maersk: AI-Enhanced Logistics Operations

A.P. Moller-Maersk, one of the world's largest shipping and logistics companies, provides a compelling illustration of how AI can enhance existing operational skills rather than replace them. The company deploys self-learning technologies across its established supply chain functions areas where it already possesses deep expertise but where AI's pattern-recognition strengths can unlock new efficiencies. Specifically, Maersk uses AI-powered digital twins to simulate port terminal congestion and routing scenarios before committing physical resources, predictive maintenance models that detect vessel equipment faults weeks in advance, and machine-learning algorithms that optimize fuel consumption across its global fleet of hundreds of ships. Currently, AI is applied to roughly 15–20% of the company's logistics tasks, but leadership has articulated an ambition to scale coverage to 70–80% within five to seven years. Crucially, the deployment targets existing functions, warehouse orchestration, contract management, billing accuracy, and fleet routing, rather than creating entirely new capabilities. This approach aligns with the framework's recommendation to start by enhancing existing skills before venturing into novel ones (Maersk Insights 2024).

5.3.1.2. New Skills — Morgan Stanley: AI-Powered Knowledge Retrieval and Meeting Intelligence

Morgan Stanley's AI adoption represents a textbook case of building entirely new internal capabilities that did not previously exist within the organization. In partnership with OpenAI, the wealth management giant developed two AI tools that fundamentally expanded what its 16,000 financial advisors could do. The first, launched in September 2023, is a GPT-4-powered assistant that enables instant retrieval across more than 100,000 internal research documents, investment reports, and market commentaries. Before this tool, advisors could realistically access only about 20% of the firm's collective intellectual capital; afterward, that figure jumped to approximately 80%. The second tool, "AI @ Morgan Stanley Debrief," introduced in mid-2024, created an automated meeting-intelligence function that had never existed: with client consent, it generates notes, surfaces action items, drafts follow-up emails, and integrates summaries directly into Salesforce CRM. Adoption reached 98% of advisor teams, and executives partly attributed record net new assets of \$64 billion in Q3 2024 to these new AI-driven skills (Morgan Stanley 2024).

5.3.2. Deployment domains -> External offerings

5.3.2.1. Existing Offerings — Samsung: Galaxy AI Embedded in Existing Smartphones

Samsung's approach to AI in its product portfolio illustrates how a company can substantially enhance existing market offerings without creating an entirely new product category. Beginning with the Galaxy S24 series in January 2024, Samsung integrated a comprehensive AI suite branded "Galaxy AI" directly into its flagship smartphone line. The features include real-time language translation during phone calls (Interpreter), AI-powered photo editing that can reposition objects or fill in backgrounds, intelligent writing assistance that adapts to context, call screening with AI-generated summaries, and context-aware on-screen suggestions that anticipate user needs. By the Galaxy S26 launch in February 2026, CEO TM Roh positioned the device as an "agentic phone," with Galaxy AI functioning as an intelligent operating-system layer across Samsung's entire existing ecosystem of phones, tablets, watches, and earbuds. The strategic logic is clear: rather than developing a separate AI product, Samsung enriched its established product lines, leveraging its enormous installed base as both a distribution channel and a data-collection network for continuous AI improvement (Samsung Newsroom 2024).

5.3.2.2. New Offerings — Adobe: Firefly Generative AI Creative Studio

In contrast to Samsung's enhancement strategy, Adobe's launch of Firefly in March 2023 represents the creation of an entirely new market offering, a product category that had never existed in Adobe's portfolio. Firefly is a standalone family of generative AI models and web application for AI-powered image, video, and audio creation. What makes Firefly strategically distinctive is that it was designed to be commercially safe from the ground up, trained exclusively on Adobe Stock's licensed content and public-domain material, thereby addressing the copyright concerns that plague competitors. By October 2024, users had generated over 13 billion images through the platform, and 90% of Firefly's web-app users were entirely new to Adobe demonstrating that the product genuinely expanded Adobe's addressable market rather than simply cannibalizing existing Photoshop or Illustrator customers. This is precisely the kind of new offering the framework envisions: one that creates a differentiated first-mover advantage through a novel AI-powered product while requiring significant R&D investment (Adobe 2023).

5.3.3. Competitive advantage levers -> Positioning

5.3.3.1. Higher Customer Value — Spotify: AI-Driven Hyper-Personalization

Spotify demonstrates how AI can be the central engine of customer value creation in a digital platform business. The streaming service uses machine learning to deliver hyper-personalized music, podcast, and audiobook recommendations to more than 600 million users worldwide. Its AI-powered features, Discover Weekly playlists, mood-adaptive "daylists" that shift throughout the day, and an AI DJ that

provides contextual spoken commentary between songs, process billions of listening signals including genre preferences, tempo, mood patterns, time of day, skip behavior, and social listening data. The result is that roughly 30% of all streams on Spotify now originate from algorithmically recommended content rather than deliberate user searches. This level of personalization creates substantial customer value by reducing the cognitive effort of music discovery and creating a sense that the platform uniquely “understands” each listener. Spotify posted its first full-year operating profit in 2024, with analysts crediting AI-driven engagement as a key factor in subscriber retention and advertising revenue growth (Abraham and Edelman 2024).

5.3.3.2. Lower Price — Ocado: AI Robotics Cutting Grocery Fulfilment Costs

UK-based Ocado Group offers a powerful example of how AI can dramatically reduce operating costs, enabling lower prices that would otherwise be impossible in a structurally challenging market online grocery delivery. Ocado’s Smart Platform deploys an AI “air traffic control” system that orchestrates thousands of warehouse robots moving at high speed across a grid, machine-learning demand forecasting that minimizes food waste, and AI-powered robotic picking arms that handled over 30 million items in 2024. Collectively, these technologies reduce the need for manual labor by up to 50% and enable the fulfilment of a typical 50-item grocery basket in under five minutes. Ocado licenses this technology to retail partners including Kroger in the United States and Marks & Spencer in the United Kingdom, giving them access to cost efficiencies they could not develop independently. The company targets £150 million in annual cost savings by 2027, positioning its AI-powered logistics as a path to making online grocery delivery profitable at scale, a goal the industry has long struggled to achieve (Shabong and Davey 2025).

5.3.4. Competitive advantage levers -> Defense

5.3.4.1. Data Protection — Apple: Privacy-First AI as a Competitive Moat

Apple’s AI strategy offers a distinctive illustration of how data protection can be transformed from a compliance requirement into a durable competitive advantage. The company built its entire AI framework, branded “Apple Intelligence”, around the principle that user data must be protected at every stage of AI processing. The cornerstone is Private Cloud Compute (PCC), a purpose built cloud AI infrastructure where data is encrypted end-to-end, never stored on servers, never accessible to Apple employees, and processed on custom Apple silicon servers with no persistent storage and no remote shell access. Every computation is cryptographically verifiable, meaning independent security researchers can confirm that Apple’s privacy promises are technically enforced rather than merely stated in a privacy policy. Apple opened PCC to public security researchers and launched bug-bounty programs to stress-test the system. This approach creates what analysts describe as a “privacy moat”, a structural competitive advantage that data-dependent rivals like Google or Meta cannot easily replicate without fundamentally redesigning their business models (Apple Newsroom 2024).

5.3.4.2. Upscaling — Tesla: Interconnected AI Flywheel Across Vehicles, Robots, and Energy

Tesla operates what is arguably the most powerful example of AI upscaling in the corporate world, a self-reinforcing flywheel that mutually connects AI systems across its electric vehicles, humanoid robots, and energy products to generate compounding network effects. The company's fleet of over 7 million vehicles acts as a global sensor network, collecting petabytes of real world driving data every day. This data feeds into training Full Self-Driving neural networks, which in turn improve the driving experience, driving more vehicle sales, which generates even more training data. The same vision-based, end-to-end AI stack developed for vehicles transfers directly to the Optimus humanoid robot, creating enormous R&D leverage, advances in one domain automatically benefit the other. Meanwhile, Tesla's Autobidder AI agents optimize grid-scale battery trading in real time. Each domain reinforces the others in a virtuous cycle that competitors would need to match across multiple industries simultaneously to replicate a near impossible task that illustrates the framework's emphasis on interconnecting AI systems to make imitation complex and costly (Kitishian 2025).

5.3.5. Profit model levers -> Revenue model

5.3.5.1. Existing Streams — Stitch Fix: AI-Boosted Styling Recommendations Lifting Revenue

Stitch Fix, the online personal styling service, demonstrates how AI can reinvigorate existing revenue streams without requiring entirely new business models. The company's algorithms power personalized clothing recommendations, inventory optimization, and a generative-AI virtual try-on feature that lets customers visualize garments on a digital avatar before committing to a purchase. These AI capabilities have driven nine consecutive quarters of average order value (AOV) growth up roughly 10% year-over-year in Q1 FY2026, and lifted revenue per active client to \$559. AI-powered merchandising also improved "keep rates," the percentage of shipped items that customers choose to retain, by better matching individual style preferences with available inventory. The financial result has been significant: after twelve consecutive quarters of declining revenue, Stitch Fix returned to year-over-year revenue growth of 7.3%, demonstrating that AI applied intelligently to existing business mechanics can reverse negative trajectories without fundamentally changing what the company sells or how customers pay (Wassel 2025).

5.3.5.2. New Streams — Honeywell: Forge AI-as-a-Service Platform

Honeywell's creation of the Forge platform illustrates how a traditional industrial hardware conglomerate can use AI to generate entirely new software-based revenue streams. Historically, Honeywell monetized physical products, thermostats, avionics systems, industrial control equipment. With Forge, the company developed an IoT platform that sells AI-enabled applications as a subscription service to external customers across aerospace, utilities, building management, and manufacturing. The platform leverages decades of proprietary operational-technology data combined with machine learning and digital twins to provide predictive maintenance insights, energy

management optimization, and autonomous operations capabilities. Forge now offers more than 30 AI-enabled applications, connects over 100 million assets globally, and Honeywell has set a target of \$1.8 billion in recurring Forge revenue by 2027. This represents a fundamental strategic shift from selling hardware at a one-time price to monetizing AI-powered software through ongoing subscription relationships exactly the kind of new revenue stream the framework describes (Shittu 2021).

5.3.6. Profit model levers -> Cost model

5.3.6.1. AI Automation — Klarna: AI Chatbot Replacing 700 Full-Time Agents' Workload

Swedish fintech company Klarna provides one of the most dramatic real-world illustrations of AI automation's impact on cost structures. In February 2024, Klarna deployed an OpenAI-powered AI chatbot that, within its first month of global operation, handled 2.3 million customer service conversations representing two-thirds of all customer chats across 23 markets in 35 languages. The AI performed work equivalent to approximately 700 full-time human customer service agents. Beyond sheer volume, the quality metrics were striking: resolution time dropped from an average of eleven minutes to under two minutes, and repeat inquiries fell by 25%, suggesting that the AI was not merely deflecting customers but actually resolving their issues. The financial impact was projected at \$40 million in profit improvement for 2024. Following deployment, Klarna reduced its workforce by roughly 700 employees through natural attrition and implemented a hiring freeze. However, the story also carries a cautionary lesson: by mid-2025, Klarna's CEO acknowledged that the company had gone too far with automation and began rehiring human agents for complex cases, underscoring the framework's warning that augmentation is often preferable to full substitution (Klarna 2024).

5.3.6.2. AI Augmentation — Goldman Sachs: GS AI Assistant for 46,000 Employees

Goldman Sachs deployed its proprietary GS AI Assistant firmwide to all 46,000-plus employees in mid-2025, making it one of the most comprehensive AI augmentation rollouts in the financial services industry. After a pilot phase with 10,000 staff members, the generative AI tool, which accesses approved large language models including GPT-4, Gemini, and Claude behind Goldman's firewall, was extended across investment banking, wealth management, research, and engineering divisions. The assistant helps employees summarize complex documents, draft client communications, analyze large datasets, generate code, and prepare presentations. Engineers reported productivity gains of up to 20%. Critically, Chief Information Officer Marco Argenti emphasized that the assistant is designed to augment rather than replace human work. Employees retain full decision-making authority; the AI handles time-consuming preparatory tasks so that bankers and analysts can focus on higher-value judgment calls. This represents the framework's ideal of human and machine collaboration: each side concentrating on what it does best, with AI handling information processing while humans provide strategic thinking and relationship management (Hugh 2025).

5.3.7. Implementation -> Trust and validation

5.3.7.1. *Pure Performance Focus — Shell: AI Predictive Maintenance Across 10,000+ Assets*

Shell's deployment of AI for predictive maintenance across its global operations exemplifies the "pure performance" black box doctrine, an approach where algorithmic outputs are evaluated solely by their accuracy, without requiring stakeholders to understand the model's internal reasoning. Shell partnered with C3.ai to deploy machine-learning algorithms across more than 10,000 pieces of equipment globally, including offshore drilling rigs, refineries, and pipeline networks. The AI system continuously ingests real-time IoT sensor data vibration patterns, temperature readings, pressure fluctuations, flow rates, and assigns probability-of-failure scores to individual assets, allowing maintenance teams to prioritize interventions before breakdowns occur. Engineers simply act on the alerts: if the system flags a compressor as high risk, it gets inspected, regardless of whether the maintenance team understands which specific sensor patterns triggered the warning. The system reduced unplanned downtime by 20–45% and generated estimated savings of hundreds of millions of dollars annually. This pure performance approach works because equipment failures, while costly, do not personally affect end consumers, making explainability less critical than prediction accuracy (Rerupion 2022).

5.3.7.2. *Expert Understandability — PathAI: AI-Assisted Digital Pathology for Cancer Diagnosis*

PathAI's development of AI-powered digital pathology software illustrates why certain deployment contexts demand expert understandability rather than a pure performance approach. The company's flagship product, AISight Dx, uses deep learning to analyze digitized tissue slides, detecting and classifying cellular abnormalities that may indicate cancer. However, unlike Shell's maintenance AI, the stakes here directly affect human patients, a missed detection or a false positive can alter the course of medical treatment. For this reason, AISight Dx is explicitly designed as a decision-support tool: pathologists must review, interpret, and validate the AI's highlighted findings before rendering a clinical diagnosis. The system identifies suspicious regions and quantifies biomarkers, but the final diagnostic judgment remains with the human expert. PathAI received FDA clearance in 2022, and major laboratories including Labcorp and Quest Diagnostics adopted the platform precisely because domain experts can understand and verify AI outputs. This reduces diagnostic variability while keeping the expert firmly in the decision loop, a design choice that directly reflects the framework's expert understandability doctrine (Taylor 2026).

5.3.7.3. *Nonexpert Understandability — Upstart: Plain-Language AI Lending Explanations for Consumers*

Upstart, an AI-powered lending platform, demonstrates the nonexpert understandability doctrine in a context where task stakeholders, loan applicants, are personally affected by AI decisions but lack the technical expertise to evaluate algorithmic logic. Upstart's machine learning models assess creditworthiness using over 1,600 data points beyond traditional credit scores, including education

history, employment patterns, and cost-of-living variables. When the algorithm denies a loan application, the company uses SHAP (SHapley Additive exPlanations) values to identify which variables most influenced the decision. These technical outputs are then translated into plain language Adverse Action Notices. For example, telling a denied applicant that “there is a high number of recent inquiries reported in your credit file” rather than providing an opaque “credit history” explanation. This approach directly addresses regulatory requirements from the Consumer Financial Protection Bureau (CFPB) that AI-driven credit decisions must be explained in terms that everyday consumers can understand. Upstart’s case illustrates that nonexpert understandability is not merely a design preference but often a legal and regulatory necessity (Upstart Network 2021).

5.3.8. Implementation -> Technological assets

5.3.8.1. IT Assets — *Rolls-Royce: Massive Data Infrastructure for IntelligentEngine*

Rolls-Royce’s AI journey in aerospace underscores how substantial IT infrastructure investments are often prerequisites for meaningful AI deployment. The company’s vision, called “IntelligentEngine,” aims to make every jet engine a connected, self-learning system, but realizing this vision required building an enormous data backbone from scratch. Rolls-Royce embedded thousands of IoT sensors into its installed base of more than 13,000 civil aerospace engines, constructed cloud-based data repositories on Microsoft Azure Databricks, and deployed high-powered GPU clusters for model training. To appreciate the scale: a single fan-blade manufacturing facility generates approximately three petabytes of data per year. The company built automated data pipelines, its “Blue Data Thread”, to aggregate real-time sensor readings, flight telemetry, and maintenance records into a central data lake. This infrastructure underpins AI capabilities like the “Signature Analyzer” for defect prediction and an Intelligent Borescope that accelerated fault identification from days to near real-time. Without these foundational IT investments, no amount of algorithmic sophistication could have produced results (Microsoft 2025).

5.3.8.2. Non-IT Assets — *Accenture: \$3 Billion AI Training and Cultural Transformation*

Accenture’s AI strategy provides a vivid example of how non-IT assets training, cultural change, and organizational restructuring can be just as critical as technology investments. In 2023, the consulting giant committed \$3 billion to its Data & AI practice, followed by an additional \$1 billion in 2024 for its LearnVantage upskilling platform, which included the acquisition of online learning provider Udacity. The company trained over 550,000 of its approximately 780,000 employees in generative AI fundamentals and nearly doubled its AI and data talent from 40,000 to 77,000 professionals. But the most striking move came in February 2026, when Accenture escalated its cultural transformation by tying promotions for senior staff to demonstrated regular AI tool usage effectively making AI fluency a career requirement rather than an optional skill. This comprehensive investment in human capital, organizational design, and cultural change management illustrates the framework’s emphasis on non-

IT assets. Technology alone does not drive AI adoption; people must be willing and able to use it, and organizational structures must incentivize its application (Burleigh 2026).

5.3.9. Adaptation mechanisms -> Time pacing

5.3.9.1. Short-Term / Radical — *Shopify: CEO Mandates AI-First Culture Overnight*

Shopify's transformation in April 2025 represents one of the most aggressive short-term AI mandates in recent corporate history. CEO Tobi Lütke issued a public memo declaring that reflexive AI usage was now a baseline expectation for every employee at the company. The directive went further: all teams were required to demonstrate why AI could not perform a task before requesting additional headcount or budget for new hires. AI competency was immediately integrated into formal performance reviews and staffing decisions, effectively repositioning Shopify from an AI-enabled company to an AI-native organization virtually overnight. The results were measurable within months: AI-driven traffic to Shopify storefronts surged seven-fold, and AI-attributed purchases increased eleven-fold. This radical approach illustrates the framework's observation that short-term strategies, while risky and costly, can yield powerful first-mover advantages, particularly for technology-native companies with already-digitized processes. However, such speed leaves little room for experimentation or error, making it best suited for organizations with strong digital foundations (Nolan 2025).

5.3.9.2. Long-Term / Incremental — *Toyota: Decade-Long Gradual AI Embedding*

Toyota exemplifies the patient, incremental time horizon that the framework recommends for traditional firms with established processes and structures. The company's AI journey began with the founding of the Toyota Research Institute (TRI) in 2016, a dedicated research entity tasked with exploring AI applications across manufacturing, safety, and mobility. Over the following decade, Toyota gradually embedded AI across its operations: predictive quality-control systems in manufacturing saved over 10,000 labor hours annually across ten Japanese factories, while advanced driver-assistance systems adopted a "human amplification" philosophy, deploying AI that assists drivers step by step rather than pursuing all-or-nothing autonomous driving. In 2025, Toyota launched its GAIA (Global AI Accelerator) program to scale proven AI use cases across eleven company-wide categories. This decade-long progression from R&D exploration to scaled deployment demonstrates the advantages of incremental approaches: each phase built organizational knowledge, reduced risk, and refined strategy based on real operational experience luxuries that radical short term approaches sacrifice for speed (Deloitte Insights 2025).

5.3.10. Adaptation mechanisms -> Sensing & adjustment

5.3.10.1. Internal Signals — *Mastercard: Hackathon-as-a-Process Innovation Pipeline*

Mastercard has developed a systematic mechanism for detecting internal AI innovation signals through what it calls a "hackathon as a process" model. Rather than organizing occasional one-off

innovation events, the company runs monthly “Ideabox” hackathons and annual “Discovery Days” programs that function as a structured innovation pipeline. In one recent year, the Discovery Days program drew 80 teams from employees across 26 offices in 13 countries. The process follows a clear sequence: employees pitch ideas, innovation leaders evaluate and select the most promising concepts, and winning creators are pulled from their regular roles for full-time incubation, transforming raw ideas into minimum viable products. Mastercard also runs “AI Takeover” days and bespoke AI learning sessions across all organizational levels and functions. This creates a continuous internal sensing mechanism that surfaces employee-generated AI opportunities, the kind of internal change signals the framework identifies as essential for staying ahead of technological shifts. Employees who work with AI daily are indeed well positioned to spot innovative applications (Sheopuri and Borgonovo 2024).

5.3.10.2. Industry Signals — L’Oréal: AI TrendSpotter for Beauty Market Intelligence

L’Oréal provides a sophisticated example of how a company can systematically monitor industry-specific change signals using AI itself as the sensing tool. The company’s Beauty Tech Accelerator developed TrendSpotter, an AI-powered platform that uses a dedicated Trend Detection Engine to continuously scan social media conversations, beauty blogs, influencer content, celebrity activity, and scientific publications. The system identifies emerging beauty trends, new ingredients, textures, packaging innovations, lifestyle shifts, six to eighteen months before they become mainstream consumer expectations. The platform’s signals feed directly into L’Oréal’s Prospective & Consumer Intelligence division, its R&I (Research & Innovation) laboratories, and its Marketing teams, transforming trend monitoring from a periodic manual exercise into a continuous, AI-automated competitive intelligence capability. This approach is particularly relevant in the fast-moving consumer goods sector, where customer preferences shift rapidly and the ability to anticipate, rather than merely react to trends can determine whether a product launch succeeds or misses the market window entirely (L’Oréal 2024).

5.3.10.3. Industry-Independent Signals — Novartis: Biome Cross-Industry Technology Scouting

Novartis scouts for AI innovations outside its own pharmaceutical industry through the Novartis Biome, a global network of 15 digital innovation hubs established in 2018 that bridges the pharma world with non-traditional technology partners. The rationale is explicit: as co-founder Robin Roberts noted, the vast majority of disruptive technologies are unlikely to originate from within big pharma companies. The Biome issues cross-industry innovation challenges through its HealthX World Series, operates a digital venture capital fund (dRx Capital) that monitors emerging technology trends across sectors, and actively seeks partnerships with AI start-ups working on computer vision, natural language processing, and data analytics, regardless of their original industry focus. In 2019, Novartis formalized a multiyear AI alliance with Microsoft, explicitly designed to import data science capabilities from the technology sector into pharmaceutical R&D workflows. This represents the framework’s industry-independent change signals: scientific breakthroughs at research institutions,

start-ups, and technology platforms outside a firm's traditional competitive landscape that can profoundly reshape strategic possibilities (Novartis 2019).

5.3.11. Strategic complementarity

5.3.11.1. *Hermès: Deliberately Limiting AI to Protect Artisanal Identity*

Hermès, the French luxury house, provides a compelling illustration of strategic fit achieved through deliberate AI restraint rather than aggressive AI adoption. In its 2025 shareholder filing, Hermès clarified that it uses AI only in limited back-end applications, IT service optimization, supply chain support, and internal reporting, while explicitly stating that core creative and artisanal processes will remain human-led and that the company does not foresee AI substituting its métier-specific skills. An AI Governance Committee was established in 2025 specifically to ensure that AI never encroaches on craft. This strategic restraint is not a technology lag but a deliberate competitive calculation: as automation increasingly commoditizes mass-produced goods, Hermès bets that verifiably handcrafted products will become more valuable, not less. The refusal to automate core processes is itself the competitive strategy, precisely mirroring the framework's warning that AI adoption can destroy rather than create customer value when it conflicts with what customers explicitly prize (TFL 2025).

6. Conclusions

This study is set out to address the gaps that have become increasingly pressing as firms worldwide race to adopt artificial intelligence: the absence of systematic, strategy level guidance for integrating self-learning technologies into business operations. The central argument developed throughout this work is that contemporary AI systems, by virtue of their unique self-learning abilities, require a different strategic approach than the one traditionally applied to digital technologies.

To this end, we introduced the AI Business Strategy Compass, a practitioner-oriented framework built around five interrelated questions that any firm serious about AI must answer. A recurring theme across all five dimensions is the importance of strategic complementarity. Each decision a firm makes about AI deployment, competitive positioning, financial capture, implementation, or timing must reinforce the others. Isolated AI initiatives, like a pilot project here, a chatbot there, rarely produce lasting impact unless they are part of a coherent, mutually reinforcing plan.

At the same time, the paper urged both scholars and practitioners to maintain a balanced perspective on AI. The technology is undeniably powerful, but it is not universally applicable. Self-learning systems remain poorly suited to tasks requiring deep contextual awareness, genuine creativity, or socioemotional sensitivity. Moreover, AI adoption can generate significant negative side effects, power asymmetries between firms, ethical and legal complications, workforce displacement and resistance, and security vulnerabilities. When strategists fail to weigh these limitations and risks

properly, AI adoption can become counterproductive. The history of the field itself, marked by several so-called "AI winters" where inflated expectations gave way to widespread disappointment (Russell and Norvig 2022), serves as a cautionary reminder.

Looking ahead, the framework presented here should be understood as a starting point rather than a final word. Future empirical research, large-scale surveys, longitudinal case studies, cross-industry comparisons, can test, refine, and extend the AI Business Strategy Compass. It would be particularly valuable to identify strategy archetypes suited to specific organizational contexts, to compare firms using this framework with those relying on conventional approaches, and to examine how technology leaders' actual strategies align with or diverge from the patterns described here. The field of AI will continue to evolve in ways that are difficult to predict, and the strategic frameworks we use to manage it must evolve accordingly. What will not change, however, is the fundamental need for firms to approach AI not as a technological curiosity or a passing trend, but as a strategic choice that demands the same rigor, coherence, and continuous reassessment as any other element of business strategy.

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