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Strategic Management in the AI Era: Gaining and Sustaining Competitive Advantage

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ
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«Δηλώνω υπεύθυνα ότι η διπλωματική εργασία για τη λήψη του μεταπτυχιακού τίτλου σπουδών, του Πανεπιστημίου Πειραιώς, στη Διοίκηση Επιχειρήσεων - Ολική Ποιότητα, με Διεθνή Προσανατολισμό **«Strategic Management in the AI Era: Gaining and Sustaining Competitive Advantage»** έχει συγγραφεί από εμένα αποκλειστικά και στο σύνολό της. Δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού προγράμματος ή προπτυχιακού τίτλου σπουδών, στην Ελλάδα ή στο εξωτερικό, ούτε είναι εργασία ή τμήμα εργασίας ακαδημαϊκού ή επαγγελματικού χαρακτήρα.

Δηλώνω επίσης υπεύθυνα ότι οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης εργασίας, αναφέρονται στο σύνολό τους, κάνοντας πλήρη αναφορά στους συγγραφείς, τον εκδοτικό οίκο ή το περιοδικό, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο. Παράβαση της ανωτέρω ακαδημαϊκής μου ευθύνης αποτελεί ουσιώδη λόγο για την ανάκληση του πτυχίου μου».

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Strategic Management in the AI Era: Gaining and Sustaining Competitive Advantage

Gerardis Emmanouil

Keywords: Artificial Intelligence (AI), Competitive Advantage, Human-AI Collaboration, Industry 4.0/Industry 5.0.

ABSTRACT

This thesis examines how Artificial Intelligence (AI) reshapes the foundations of competitive advantage in the digital era. Through a narrative literature review, it integrated classical strategic management theories, such as the Resource-Base View, the Knowledge-Based View and Dynamic Capabilities, with emerging technological developments including Data Science, Internet of Things (IoT), Cyber-Physical Systems (CPS), and Generative AI. The study shows that competitive advantage increasingly depends on a firm's ability to combine data, technology, and human expertise into adaptive and continuously evolving capabilities.

Across sectors such as manufacturing, finance, healthcare, retail and professional services, AI enables predictive maintenance, personalization, enhanced decision-making, and new data-driven business models. At the same time, the research highlights key challenges related to algorithmic bias, data quality, explainability, privacy, and the risk of organization dehumanization. These issues underline the need for strong governance structure and responsible AI deployment.

The thesis also emphasized that human capital remains essential for sustained advantage, particularly as organizations transition toward the human-centric principles of Industry 5.0. Human-AI collaboration, continuous reskilling, and strategic HR practices are identified as critical for managing the emerging hybrid workforce. Overall, the study concluded that AI alone rarely creates lasting differentiation; sustainable competitive advantage arises when AI is combined with proprietary data, deep organization integration, ethical governance, and human-centred leadership.

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List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CPS	Cyber-Physical Systems
DC	Dynamic Capabilities
DL	Deep Learning
ERP	Enterprise Resource Planning
GenAI	Generative Artificial Intelligence
GDPR	General Data Protection Regulation
HITL	Human-in-the-Loop
HR	Human Resources
HRM	Human Resource Management
IoT	Internet of Things
IP	Intellectual Property
KBV	Knowledge-Based View
KPI	Key Performance Indicator
L&D	Learning and Development
LLM	Large Language Model
ML	Machine Learning
NLP	Natural Language Processing
R&D	Research and Development
RBV	Resource-Based View
ROI	Return of Investment
SHRM	Strategic Human Resource Management
SME	Small and Medium-Sized Enterprises
VRIO	Value, Rarity, Imitability, Organization
XAI	Explainable Artificial Intelligence

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Chapter 1
Introduction

1.1 Background and Context

The contemporary competitive landscape is being reshaped by the rise of the "fourth science paradigm", in which data - intensive discovery and large - scale computational analysis have become central to organizational success (Cao, 2018; Elshawi et al., 2018). Competitive advantage, traditionally defined as a unique set of attributes or strategic actions that enable a firm to outperform its rivals (Wang, 2013), was historically grounded in distinctive strategies that were costly or difficult for competitors to imitate (Assensoh-Kodua, 2019; Hamadamin and Atan, 2019, Kuncoro and Suriani, 2018). Classic strategic tools such as SWOT analysis and Porter's Five Forces once provided the dominant frameworks for industry positioning, yet these static models are increasingly viewed as inadequate for the fast moving, technology - driven dynamics of the digital era (Nonaka and Takeuchi, 2021). As a result, modern strategy has shifted inward, emphasising the internal environment, particularly the resources, knowledge and adaptive capabilities that allow firms to thrive under rapid technological change.

This shift is captured through several foundational theoretical perspectives. The Resource - Based View (RBV) argues that superior performance stems from the effective deployment of firm - specific resources and capabilities rather than external market conditions (Hossain et al., 2022, Kero and Bogale, 2023; Wang 2013). The Knowledge - Based View extends this logic by positioning knowledge as the most strategically significant resource, one that grows in value through use and is inherently resistant to imitation (Assensoh-Kodua, 2019; Chowdhury et al., 2024; Cuthbertson and Furseth, 2022). Complementing these perspectives, the Dynamic Capabilities (DC) framework conceptualises a firm's ability to integrate, reconfigure and renew its competencies in response to volatile environments, preventing resource obsolescence and enabling continuous adaptation (Doz, 2020; Kero and Bogale, 2023; Sjödin et al., 2023).

Within this evolving strategic context, Artificial Intelligence (AI) has emerged as a central-meta capability. Innovation now functions as the mechanism through which static assets are transformed into dynamic capabilities (Cuthbertson and Furseth, 2022), and Data Science, integrating statistics, computing and managerial insight, provides the analytical foundation for extracting value from high - velocity digital environments (Cao, 2018; Elshawi et al., 2018). This is reinforced by the evolution of the Internet of Things (IoT) into Cyber - Physical Systems (CPS) and the Internet of Intelligent Things (IoIT), which operate as distributed sensory networks feeding data into AI's cognitive core (Gupta and Gupta, 2016; Jackson et al., 2024; Oliveira et al., 2024). In this sense, AI is no longer simply a technological tool but a strategic organizational capability, a data driven ecosystem that enhances human decision - making by interpreting external signals, learning from experience and adapting behaviour (Jaiswal et al., 2022; Sjödin et al., 2023). The rise of Generative AI (GenAI), powered by Large Language Models (LLMs) and architectures such as Transformers, GANs and VAEs, further extends this capability by enabling "artificial creativity", shifting AI's role from prediction to the generation of novel content and reasoning (Gao et al., 2024; Jackson et al., 2024; Oliveira et al., 2024).

Viewed through the Dynamic Capabilities lens, AI algorithms themselves are increasingly commoditised; the strategic advantage lies in a firm's ability to sense emerging opportunities, seize resources and transform organizational structures to support continuous technological renewal (Hossain et al., 2022; Jorzik et al., 2024; Nonaka and Takeuchi, 2021). This capability underpins AI - Enabled Business Model Innovation (BMI), which redefines cost leadership as dynamic cost optimization (Jerab and Mabrouk, 2023; Yaiprasert and Hidayanto, 2024) and shifts differentiation from mass production to data - driven mass personalization.

These AI - driven capabilities are transforming value creation across sectors. In manufacturing and supply chains, firms are adopting "cognitive manufacturing", using Deep Learning (DL) for Predictive Maintenance (PdM) to anticipate equipment failures (Ekene Cynthia Onukwulu et al., 2021; Khedr and Rani, 2024; Peretz-Andersson et al., 2024), while autonomous agent - based AI optimizes logistics, energy use and production flows (Gao et al., 2024; Rashid and Kausik, 2024). In services and knowledge intensive industries, AI and Machine Learning (ML) are reshaping fraud detection, compliance, diagnostics, retail personalization and routine professional tasks in Professional Services Firms (PSFs) (Bezuidenhout et al., 2023; Corral de la Mata et al., 2022; Zhang et al., 2020).

Despite rapid automation, human capital remains an irreplaceable strategic asset. To sustain competitive advantage, human resources must satisfy the VRIO criteria (being valuable, rare inimitable and supported by organizational systems) (Anastasiu et al., 2020; Hamadamin and Atan, 2019; Huang et al., 2023; Kero and Bogale, 2023; Kuncoro and Suriani, 2018; Pasban and Nojedeh, 2016). As organizations integrate AI, the HR function is evolving into a form of

Institutional Entrepreneurship, redesigning structures and orchestrating resources to combine AI tools with human expertise (Chowdhury et al., 2024; Peretz-Andersson et al., 2024). With the rise of HR Analytics and predictive modeling, managerial decision - making is shifting from intuition - based to evidence - based practices, though this introduces new ethical challenges related to bias, transparency and privacy.

Ultimately, the transformation of work reflects a broader movement from the automation-driven logic of Industry 4.0 to the human centric, resilient ethos of Industry 5.0 (Poláková et al., 2023; Sowa et al., 2021). The future of work is defined not by human replacement, but by human - machine symbiosis, where AI amplifies efficiency and humans contribute contextual understanding, emotional intelligence and advanced problem solving, capabilities that remain beyond the reach of algorithms (Jaiswal et al., 2022; Poláková et al., 2023; Su et al., 2021; Sun and Song, 2025). Thriving in this environment requires organizations to move beyond viewing AI as a simple efficiency mechanism and instead develop robust conceptual frameworks for managing a hybrid workforce in which human and artificial intelligence evolve together.

1.2 Problem Statement

Artificial Intelligence (AI) is transforming the foundations of organizational competitiveness by enabling machines to perform cognitive tasks traditionally associated with human expertise (Krakowski et al., 2023). Yet research remains divided on whether AI primarily replaces or enhances human capabilities. Some scholars view AI as a substitute for human cognition, automating tasks in fields such as finance, recruitment, and medicine, while others argue that AI complements human expertise through collaborative decision-making (Krakowski et al., 2023). This ambiguity stems from AI's unique ability to learn and act autonomously, allowing it to both replace and cooperate with humans. As a result, substitution and complementarity are expected to coexist, however the mechanisms that govern their interaction remain unclear.

The rapid expansion of AI adoption across industries has intensified concerts about its impact on employment and workforce structures. Advances in data availability and computational power have accelerated AI integration in sectors such as education, healthcare, finance, and law (Sathyanarayana and Harsha, 2025). Unlike earlier automation waves that targeted manual labor, AI now affects cognitive and analytical roles, raising concerns of job displacement, deskilling, and shifting professional boundaries. Although some studies suggest that AI will reshape rather than eliminate jobs, by creating new roles focused on oversight, interpretation and ethical governance, the pace of change has shifted significant uncertainty for organizations and workers (Krakowski et al., 2023).

At a broader societal level, the anticipated “AI revolution” is expected to surpass the industrial and digital revolutions in scale and impact (Makridakis, 2017). Predictions range from optimistic scenarios of human-machine augmentation to concerns about job loss, inequality, and reduced human agency. While catastrophic outcomes remain speculative, AI-related risks cannot be dismissed given the potential societal consequences (Makridakis, 2017). The central challenge is not whether AI will transform work, but how this transformation can be managed responsibly.

Despite growing attention to these issues, a critical gap persists: existing research does not provide a clear framework for understanding how humans and AI should share control, when AI should act autonomously, and when human intervention is necessary. The coexistence of substitution and complementary demands new models of hybrid intelligence that move beyond binary debates and instead focus on dynamic, context-dependent collaboration between humans and AI systems. Addressing this gap is essential for designing sustainable workforce strategies, developing effective governance mechanisms, and ensuring that AI enhances rather than undermines human decision-making.

1.3 Research Aim and Objectives

The aim of this research is to examine how Artificial Intelligence (AI) reshapes the sources of competitive advantage by comparing the historical role of human capabilities with the emerging role of intelligent systems. The study investigates how AI is integrated across different sectors, how it transforms organizational processes and skill requirements, and whether the relationship between humans and AI is ultimately complementary or competitive.

1.4 Research Questions

To achieve this aim, the study pursues the following objectives:

- To analyse how competitive advantage has traditionally been derived from human capabilities, including cognitive skills, expertise, creativity, and decision-making.
- To examine how AI technologies generate new forms of competitive advantage, focusing on automation, data-driven decision-making, scalability, and predictive accuracy.

- To explore the integration of AI across key sectors, such as industry, healthcare and finance, and assess how AI adoptions transform work processes, roles, and organizational performance.
- To compare the contributions of humans and AI to competitive advantage, identifying the conditions under which each outperforms the other.
- To evaluate whether the relationship between humans and AI is predominantly complementary or competitive, and to identify the factors that shape this dynamic.

1.5 Scope and Delimitations

The study focuses on the strategic and organizational implications of AI adoption rather than the technical development of AI systems. It examines human-AI dynamics at the level of work processes, decision-making, and sectoral transformation. The research does not aim to predict long-term technological singularity scenarios but instead concentrates on current and near-future implications for competitive advantage and workforce structures.

1.6 Methodology Overview

This study adopts a narrative literature review methodology to examine how AI reshapes the sources of competitive advantage and the evolving relationship between human and machine capabilities. The research is based on the systematic collection, evaluation, and synthesis of academic publications from reputable scientific databases, including Google Scholar and ScienceDirect, as well as research platforms such as Consensus.

The literature search was conducted using targeted keywords related to the study's core themes, such as "strategic management and AI", "competitive advantage in the age of AI", "human vs AI capabilities", and "AI workforce transformation". Priority was given to publications from the last decade to ensure contemporary relevance, with selective inclusion of foundational theoretical works where necessary.

To organize and manage the collected sources, the reference management software Zotero was used. Zotero facilitated the systematic storage, categorization, and citation of academic materials throughout the research process, ensuring consistency and traceability across chapters.

All sources were reviewed in English to enhance accessibility and ensure consistency in terminology. During the writing process, AI tools such as Microsoft Copilot and Gemini Pro were used exclusively for grammar refinement, clarity improvements, and language polishing. These tools did not influence the conceptual development, interpretation of findings, or analytical conclusions of the study.

1.7 Thesis Structure

This thesis is structured into ten chapters, each building progressively toward an integrated understanding on how Artificial Intelligence (AI) reshapes competitive advantage and the evolving relationship between human and machine capabilities.

- **Chapter 1 - Introduction:** this chapter outlines the background, problem statement, research aim and objectives, research questions, scope, and methodological approach. It establishes the motivation for the study and introduces the central themes explored throughout the thesis.
- **Chapter 2 - Strategic Management and Foundational Concepts:** this chapter provides the theoretical foundation by reviewing core strategic management frameworks. It examines definitions and typologies of competitive advantage, dynamic capabilities theory, knowledge-based and resource-based views, traditional strategic tools and the role of innovation in sustaining long-term advantage.
- **Chapter 3 - Technological Advancements:** Defining the AI Ecosystem: this chapter maps the technological landscape underpinning modern AI. It discusses data science, big data analytics, the Internet of Things (IoT), machine learning and deep learning, and concludes with a strategic definition of AI and an overview of the generative AI ecosystem.
- **Chapter 4 - Strategic Human Resource Management and Competitive Advantage:** this chapter explores the human dimension of competitive advantage. It analyses human capital through the Resource-Based View, the role of HR in leveraging AI and data, organizational learning, upskilling and reskilling, HR analytics, and ethical considerations in AI-enabled HR practices.
- **Chapter 5 - Artificial Intelligence as a Direct Source of Competitive Advantage:** this chapter examines AI as a strategic asset. It evaluates AI through the VRIO framework, conceptualizes AI as a dynamic capability, and analyses how AI enables cost leadership, differentiation strategies, and business model innovation.
- **Chapter 6 - Artificial Intelligence in the Industrial Sector:** this chapter investigates AI applications in manufacturing and production environments. It covers predictive maintenance, asset management, supply chain optimization, and AI-driven sustainability and energy efficiency initiatives.

- **Chapter 7 - Artificial Intelligence in the Services Sector:** this chapter analyses AI adoption in key service industries, including finance and banking, healthcare, retail, and professional services. It highlights sector-specific transformations and emerging competitive advantages.
- **Chapter 8 - Artificial Intelligence vs Human:** Complementary or Competitive? : this chapter synthesizes the findings of previous chapters to examine whether AI substitutes or complements human capabilities. It discusses augmented intelligence , Human-in-the-Loop (HITL) models, automation risk, job displacement, evolving skill demands, and strategies for managing the hybrid workforce.
- **Chapter 9 - Limitations, Challenges, and Future Directions:** this chapter outlines the challenges associated with AI adoption, while also discusses the limitations of the current study and proposes directions for future research.
- **Chapter 10 - Conclusion**: the final chapter summarizes the key findings, highlights the study's contributions to theory and practice, and presents managerial and policy implications. It concludes with a final reflection on the evolving relationship between humans and AI in the pursuit of competitive advantage.

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Chapter 2
Strategic Management and Foundational Concepts

2.1 Competitive Advantage: Definition and Typology

Competitive advantage refers to the distinct set of attributes or strategic action that enable an organization to surpass its rivals (Wang, 2013). Fundamentally, this advantage is realized when a firm executes a value-creating strategy that is not simultaneously being employed by current or potential competitors (Assensoh-Kodua, 2019; Hamadamin and Atan, 2019). For such an advantage to be considered "sustainable", it must persist over the long term, remaining distinctive while proving difficult or expensive for others to duplicate (Kuncoro and Suriani, 2018).

Strategic management utilizes several theoretical lenses to explain where competitive advantage originates. The Market-Based View (MBV) argues that a firm's performance is primarily determined by external industry factors and market orientation (Wang, 2013). The MBV assesses a company's strategic position within the industry structure, utilizing tools like Porter's Five Forces to identify market power derived from entry barriers, monopoly status, and bargaining leverage (Wang, 2013). In contrast, the Resource-Based View (RBV) emphasizes a firm's internal resources as the central drivers of success (Hossain et al., 2022; Wang, 2013). To yield a sustained advantage, these resources must satisfy the VRIO criteria: they must be Valuable, Rare, Inimitable, and Organizationally supported (Gao et al., 2024; Kero and Bogale, 2023).

Complementing these views in the Dynamic Capabilities (DC) perspective, which addresses rapidly shifting environments by focusing on an organization's capacity to integrate, build, and reconfigure both internal and external competencies to maintain relevance (Hossain et al., 2022; Kero and Bogale, 2023). Furthermore, the Knowledge-Based View (KBV) acts as an extension of the RBV, suggesting that knowledge is the most strategically significant resource. Its importance lies in its uniqueness, its ability to increase through application, and the inherent difficulty competitors face in copying it (Wang, 2013).

When translating these theories into action, firms often pursue a Cost Leadership Strategy, which aims to establish the firm as the lowest-cost producer or provider within its industry (Jerab and Mabrouk, 2023). Organizations pursuing this objective concentrate on minimizing operational and production expenses to offer products or services at lower prices than rivals, all while maintaining acceptable quality standards. Success typically relies on economies of scale, producing at volume to lower per-unit-costs, as well as product standardization, efficient supply chains, and aggressive investment in automation and technology (Jerab and Mabrouk, 2023). This approach captures market share by attracting price-sensitive customers and provides a buffer during economic downturns (Jerab and Mabrouk, 2023). In this digital era, cost leadership is increasingly enhanced by predictive optimization, such as AI systems that reroute inventory in real-time to cut fulfilment costs (Dzreke, 2024)

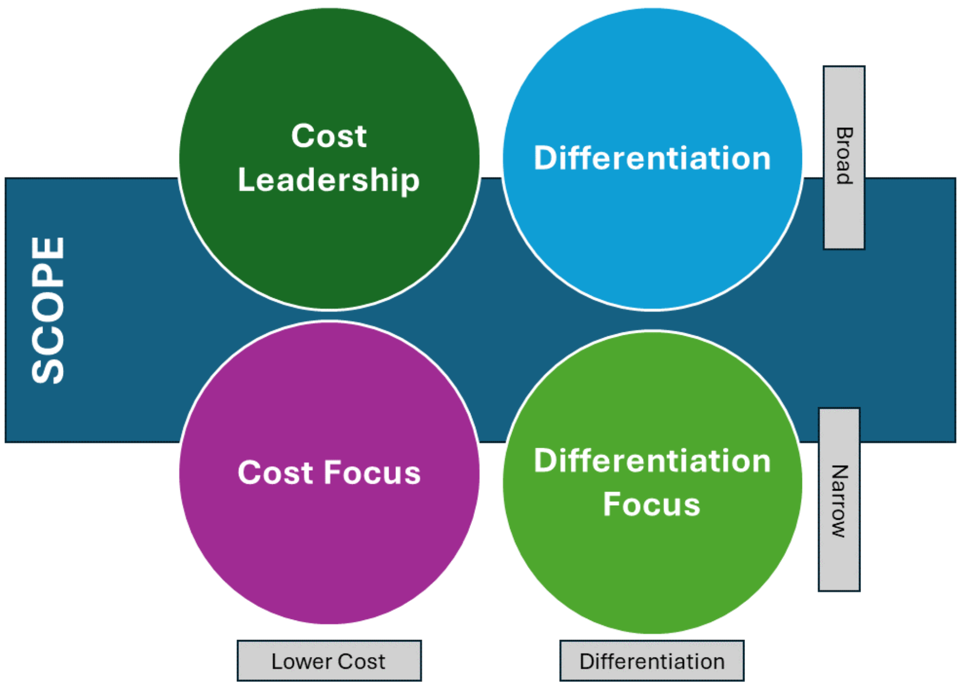

Figure 1. Porter's Generic Strategies Matrix. *This figure illustrates the four fundamental strategies for achieving competitive advantage based on the intersection of competitive scope (broad or narrow) and strategic strength (cost leadership or differentiation).* ***Source:*** *Author's own creation, based on Porter (1985).*

Conversely, the Differentiation Strategy centres on delivering unique products or services that offer superior value, thereby exceeding customer expectations (Hossain et al., 2022; Huang et al., 2023). Firms strive to secure a unique, valuable market position by configuring their activities in a way that is difficult for competitors to replicate (Borges et al., 2021; Kuncoro and Suriani, 2018). This strategy is driven by innovation, high product quality, strong brand image, distinctive technology, and superior customer service (Borges et al., 2021). By offering benefits unavailable elsewhere, organizations create high switching costs for buyers (Jerab and Mabrouk, 2023; Pangarkar and Prabhudesai, 2024). Ultimately, differentiation allows firms to command premium prices and foster deep brand loyalty (Jerab and Mabrouk, 2023). Modern differentiation often leverages algorithmic customization, such as AI engines capable of personalizing content for millions of individual users simultaneously to guarantee a unique customer experience (Dzreke, 2024).

In summary, understanding the multifaceted nature of competitive advantage, encompassing both its theoretical origins and its strategic execution through cost or differentiation, is fundamental to strategic management. While external market factors play a role, the ability to sustain these strategies over time increases toward the importance of internal firm characteristics.

2.2 Resource-Based View (RBV) and the VRIO Framework

The Resource-Based View (RBV) represents a pivotal shift in strategic management, redirecting focus from external industry structures to the firm's internal environment as the primary driver of competitive advantage (Kero and Bogale, 2023; Wang, 2013). This framework posits that organizational success is contingent upon the ability to optimally utilize a unique bundle of resources, encompassing all assets, capabilities, organizational process, and information under the firm's control (Hossain et al., 2022). The core logic of the RBV suggests that superior performance stems from sustainable advantages derived from firm-specific resources rather than general industry conditions (Wang, 2013).

This theoretical perspective rests on two fundamental assumptions: resource heterogeneity and resource immobility. Unlike earlier economic theories which assumed that firms within an industry were essentially identical, the RBV argues that companies possess divergent talents, capacities, and resources (Kero and Bogale, 2023). Furthermore, these resources are characterized by immobility; they cannot be easily transferred between organizations, often being semi-permanently tied to the firm. This stickiness prevents rivals from simply purchasing the source of a competitor's success (Kero and Bogale, 2023; Wang, 2013). Within this framework, resources are categorized into tangible assets, such as physical equipment and financial capital, and intangible assets, including brand equity, intellectual property, and internal knowledge. Strategic management scholars emphasize that intangible resources are significantly more likely to yield long-term success because they are inherently harder for competitors to identify and replicate (Kero and Bogale, 2023).

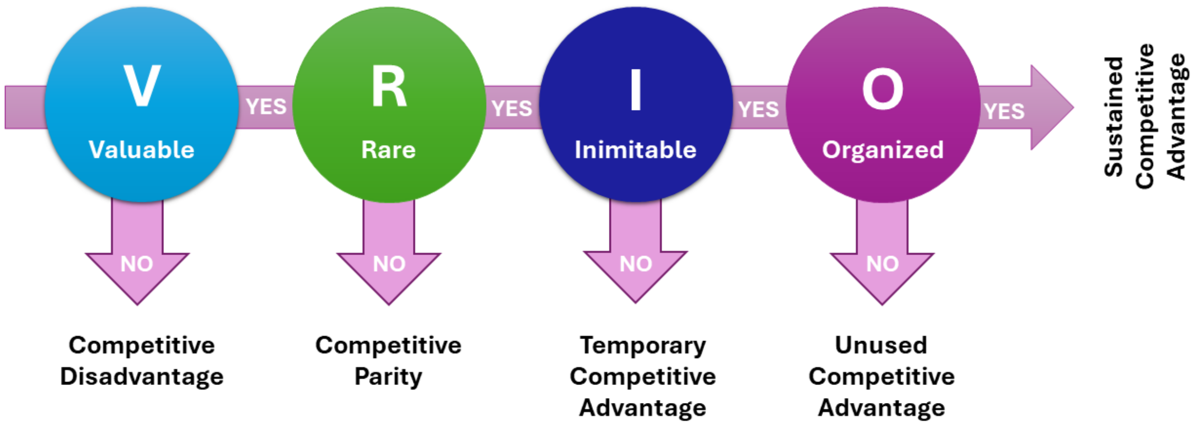

Figure 2. The VRIO Framework Decision Tree. *This flowchart illustrates the sequential criteria (Value, Rarity, Initiability and Organization) used to evaluate whether an organizational resource can generate a sustainable competitive advantage, outlining the potential competitive outcomes at each stage of the analysis.* ***Source:*** *Author's own creation, based on Barney (1991).*

To determine which specific resources contribute to a sustained competitive advantage, the VRIO framework evaluates four crucial elements: Value, Rarity, Inimitability, and Organization. First, a resource is considered **Valuable** if it enables a firm to exploit an opportunity or neutralize an environmental threat; without this, the resource merely results in a competitive disadvantage in the current market context (Kero and Bogale, 2023). Second, the resource must be **Rare**, controlled by only a small number of competing firms. If a valuable resource is ubiquitous across an industry, it leads only to competitive parity, as no single firm can leverage it to outperform others (Kero and Bogale, 2023).

The third criterion is **Inimitability**, or being "costly to imitate", meaning competitors find it difficult or expensive to duplicate the resource (Kuncoro and Suriani, 2018). This quality often stems from unique historical conditions known as path dependence, causal ambiguity (where the link between the resource and success is unclear to outsiders) or social complexity rooted in deep organizational culture (Huang et al., 2023). Finally, the resource must be Organized to capture value. Even if a firm possesses valuable, rare, and inimitable resources, it will only achieve a temporary advantage if it lacks the necessary management systems, processes, and policies to fully exploit them (Kero and Bogale, 2023).

In the contemporary digital landscape, the VRIO framework is increasingly applied to emerging assets like Artificial Intelligence and Human Capital. Data superiority and algorithmic prowess are now viewed as dynamic VRIO resources; their value is derived from faster innovation, while their inimitability is established through recursive learning loops that competitors cannot easily copy

(Dzreke, 2024). Similarly, human resource management practices that are personalized create high casual ambiguity and path dependence, effectively transforming a firm's talent pool into a unique and sustained source of competitive advantage (Huang et al., 2023).

2.3 Dynamic Capabilities (DC) Theory

Dynamic Capabilities (DC) theory describes an organization's ability to integrate, develop and reshape its internal and external competencies in response to fast-changing environments (Kero and Bogale, 2023; Sjödin et al., 2023). While the RBV emphasizes owning valuable and rare resources, DC theory explains how firms build competitive advantage specifically in volatile or unpredictable markets (Kero and Bogale, 2023). DCs are often viewed as a "meta-capability", meaning a higher-level function that enables firms to stay aligned with their environment by continually evolving their resource base rather than depending on static assets (Doz, 2020; Sjödin et al., 2023).

Literature commonly divides dynamic capabilities into three core activities: Sensing, Seizing, and Reconfiguring. Sensing involves the ability to detect emerging technologies, market shifts, and potential threats through heightened awareness and environmental scanning (Doz, 2020; Jackson et al., 2024). This includes gathering intelligence and identifying weak signals before competitors notice them (Pangarkar and Prabhudesai, 2024; Sjödin et al., 2023). After identifying an opportunity, firms move to the Seizing stage, where they mobilize resources to create new solutions and business models (Jackson et al., 2024; Sjödin et al., 2023). This stage requires timely strategic decisions and coordination across internal functions to capitalize on opportunities (Peretz-Andersson et al., 2024; Perifanis and Kitsios, 2023). The final stage, Reconfiguring (or Transforming), involves continuously renewing and restructuring organizational assets and processes to maintain competitiveness as conditions change (Jorzik et al., 2024; Sjödin et al., 2023). Effective reconfiguration helps firms overcome rigidity and adapt their operations to evolving market demands (Doz, 2020; Jackson et al., 2024).

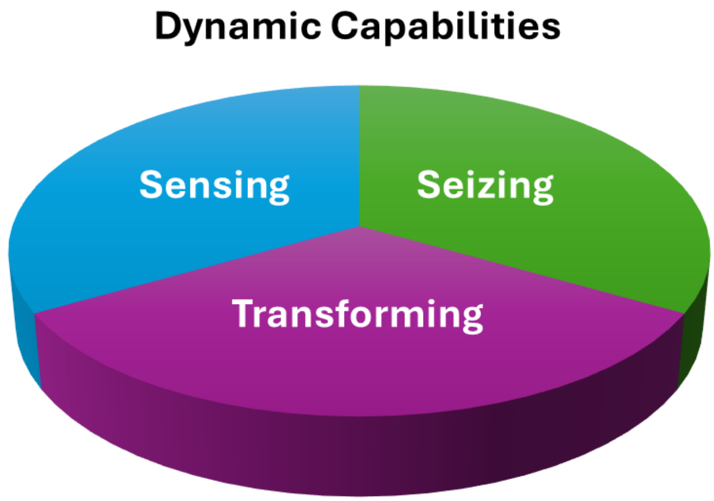

Figure 3. The Dynamic Capabilities Framework. *This diagram illustrates the continuous cycle of strategic activities (Sensing, Seizing, Transforming) that enable organizations to adapt their resources base and maintain competitiveness in changing environments.* ***Source:*** *Author's own creation, based on Teece et al. (1997).*

Recent research extends DC theory to modern VUCA (Volatile, Uncertain, Complex and Ambiguous) environments, highlighting AI as a major enabler of dynamic adaptation (Dzreke, 2024). AI functions as a "meta-capability" by enhancing the sensing process, revealing hidden patterns in large datasets that surpass human analytical abilities (Edilia and Larasati, 2023; Hosavaranchi Puttaraju, 2023). For instance, Ant Financial uses AI to analyze real-time transaction data for lending decisions, while NVIDIA exemplifies transformation by shifting from a hardware producer to an orchestrator of an AI ecosystem (Dzreke, 2024).

This adaptability is further explained through strategic agility, which consists of three components: Strategic Sensitivity (perceptual accuracy), Resource Fluidity (rapid redeployment of assets), and Collective Commitment (the leadership team's ability to make unified, bold decisions) (Doz, 2020). High-performing firms use these elements to absorb disruptions constructively, treating failures as learning opportunities that encourage new behaviours (Doz, 2020). Resource Orchestration (RO) complements this view by focusing on how managers structure, combine, and leverage resources (Peretz-Andersson et al., 2024). In manufacturing SMEs, this involves continuously acquiring AI tools and integrating them into learning capabilities that support digital transformation (Peretz-Andersson et al., 2024).

Leadership also plays a central role, as emphasized by Dynamic Managerial Capabilities (DMC) (Jaiswal et al., 2022). DMC explains how senior leaders develop and redeploy their own skills to guide strategic change across the organization (Jaiswal et al., 2022). Leaders with strong contextual awareness and the ability to avoid premature judgment are better equipped to navigate turbulent conditions (Doz, 2020; Kaggwa et al., 2024). Finally, firms are applying these capabilities to shift toward circular business models (CBMs), using “value discovery” routines to identify sustainability challenges and “value optimization” to continually reconfigure supply chains for long-term resilience (Sjödin et al., 2023).

2.4 The Knowledge-Based View (KBV)

The Knowledge-Based View (KBV) argues that a firm’s diverse knowledge base, together with its ability to generate, integrate, and manage knowledge, is the main source of superior performance and competitive advantage (Chowdhury et al., 2024; Cuthbertson and Furseth, 2022). Although it builds on the RBV, the KBV differs by asserting that knowledge is the most strategically important resource a firm can possess. This is because knowledge is unique, grows in value through use, and remains difficult for competitors to replicate (Assensoh-Kodua, 2019).

From this perspective, an organization is not simply an information-processing system but a living entity that evolves through the continuous transformation of knowledge (Nonaka and Takeuchi, 2021). Sources typically distinguish knowledge based on how accessible and complex it is. Explicit knowledge forms the visible “tip of the iceberg”: codified information stored in manuals, documents, and databases (Morandini et al., 2023; Nonaka and Takeuchi, 2021). In the digital age, explicit knowledge has become increasingly abundant and interconnected through automation (Nonaka and Takeuchi, 2021). Beneath this lies tacit knowledge, which is the much larger, hidden portion of the iceberg (Nonaka and Takeuchi, 2021). Tacit knowledge is personal, experience-based, and difficult to formalize, consisting of practical “know-how” and expert skills (Assensoh-Kodua, 2019; Morandini et al., 2023). Because tacit knowledge is socially embedded and tied to individual experience, it provides a more enduring competitive advantage than easily codified information (Huang et al., 2023; Pasban and Nojedeh, 2016). Sources also highlight Practical Wisdom (Phronesis) as a higher form of knowledge that enables leaders to make sound, ethically informed decisions (Nonaka and Takeuchi, 2021).

Organizational success depends on mobilizing these knowledge assets through the SECI model, a continuous spiral of knowledge creation. Socialization transfers knowledge from tacit to tacit through shared experiences and observation (Nonaka and Takeuchi, 2021). Externalization transforms tacit insights into explicit concepts or models (Nonaka and Takeuchi, 2021).

Combination integrates different bodies of explicit knowledge into more complex systems (Nonaka and Takeuchi, 2021). Finally, Internalization converts again explicit knowledge back into tacit understanding as individuals absorb and supply what they have learned (Nonaka and Takeuchi, 2021).

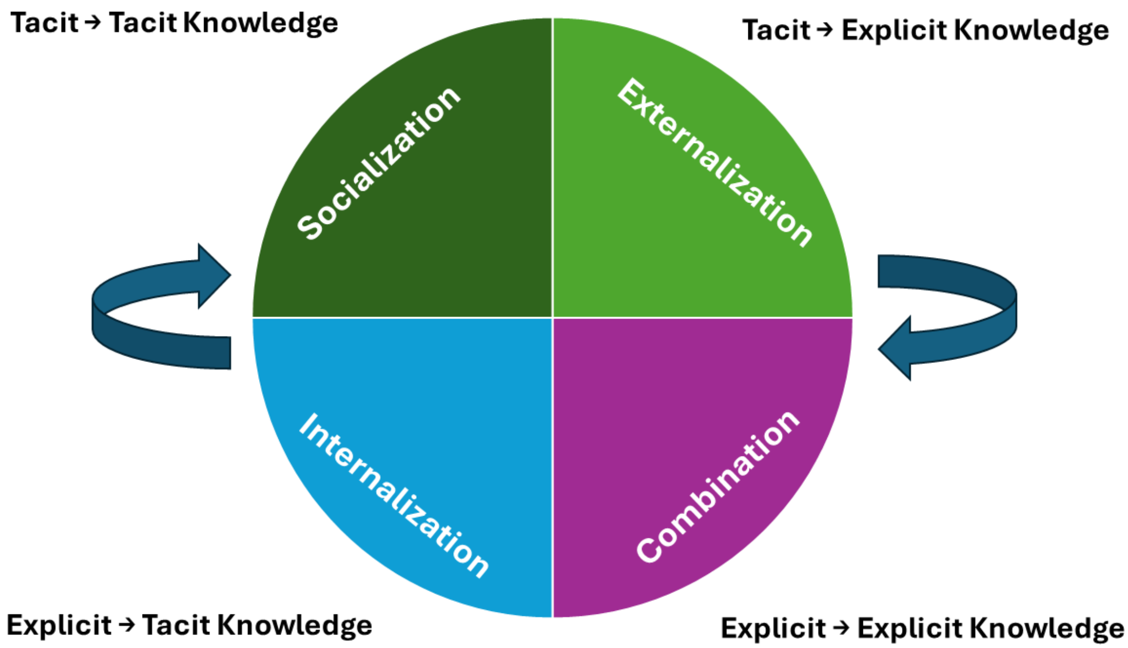

Figure 4. The SECI Model of Knowledge Creation*. This figure depicts the continuous spiral of knowledge conversion, comprising Socialization, Externalization, Combination, and Internalization, through which organizations transform tacit and explicit knowledge to drive innovation and learning.* ***Source:*** *Author's own creation, based on Nonaka and Takeuchi (1995).*

In the Big Data era, distinguishing between raw data and meaningful knowledge is essential (Nonaka and Takeuchi, 2021). Although data is often described as the "new oil", it only becomes strategically valuable when transformed into Actionable Intelligence (Elshawi et al., 2018; Hossain et al., 2022). Artificial Intelligence is highly effective at processing large volumes of explicit data and identifying hidden patterns, but it still lacks the tacit insight and emotional intelligence inherent to humans (Gao et al., 2024). As a result, competitive advantage increasingly depends on moving from descriptive insights about "what happened" to prescriptive guidance on "what should be done" (Cao, 2018). Achieving this shift requires strong Absorptive Capacity, which is the ability to identify, assimilate, and supply external knowledge for commercial benefit (Dzreke, 2024).

Despite technological advances, humans remain central to the knowledge-creation process (Nonaka and Takeuchi, 2021). Human Capital, defined as the collective skills, knowledge, and well-being of individuals, is the only resource capable of continuously developing and improving itself (Pasban and Nojedeh, 2016). To sustain competitive advantage, organizations must reduce knowledge hiding and instead cultivate a culture where knowledge is openly shared and used as a collective strength (Khogali and Mekid, 2023). By personalizing Human Resource Management (HRM) through data analytics, firms can better match individual expertise with organizational needs, creating a distinctive human capital base that is extremely difficult for competitors to imitate (Khogali and Mekid, 2023).

In summary, the KBV positions knowledge, especially tacit expertise and practical wisdom, as the most enduring source of competitive advantage in an era where data alone is no longer sufficient. While digital technologies and AI enhance a firm's ability to process explicit information, sustainable performance ultimately depends on human capital and the organization capacity to continuously create, share, and apply knowledge. Firms that cultivate open knowledge cultures, strengthen absorptive capacity, and align individual expertise with strategic goals are best equipped to transform information into meaningful action. By integrating human insight with technological intelligence, organizations can build a knowledge ecosystem that remains difficult for competitors to imitate and essential for long-term success.

2.5 Traditional Strategic Management Tools

Traditional strategic management tools, most notably SWOT analysis and Porter's Five Forces, form the basic foundations of corporate strategy, helping firms position themselves within an industry to achieve long-term superior performance (Nonaka and Takeuchi, 2021). Although these tools remain central in academic teaching, they are increasingly criticized for being static and less suited to the fast-paced, technology-driven environment of the digital age (Nonaka and Takeuchi, 2021).

Beyond these core frameworks, strategic planning incorporates several classical models to assess both macro and microenvironments. PEST/PESTEL Analysis evaluates political, economic, socio-cultural, and technological factors shaping the external landscape (Zhao, 2024; Zhylinska and Gitko, 2025). For portfolio management, the BCG Matrix categorizes business units into Stars, Cash Cows, Question Marks, and Dogs based on market share and growth potential (Zhao, 2024).

The Balanced Scorecard (BSC) further supports strategy execution by translating organizational vision into performance indicators across financial, customer, internal process, and learning dimensions (Hosavaranchi Puttaraju, 2023; Zhylinska and Gitko, 2025). Scenario Analysis complaints these tools by using historical data to model potential future outcomes under varying conditions (Zhao, 2024).

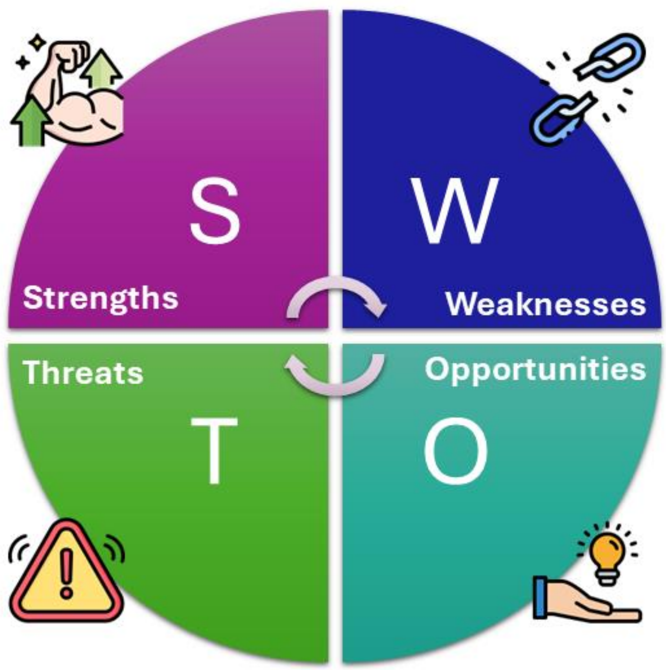

Figure 5. The SWOT Analysis Framework. *This figure categorizes the internal factors (strengths and weaknesses) and external factors (opportunities and threats) that influence an organization's strategic position and decision-making capabilities.* ***Source:*** *Personal editing using icons from Freepik, surang, iconixar, and Uniconlabs via the Flaticon platform; based on Learned et al. (1969).*

SWOT Analysis, originally developed for business case studies, examines internal Strengths and Weaknesses alongside external Opportunities and Threats (Zhao, 2024). Its academic value lies in promoting objective decision-making by helping firms identify competitors, anticipate industry trends, and reduce costs (Zhao, 2024). It is also flexible, applicable at both the corporate level and within individual business units (Zhao, 2024; Zhylinska and Gitko, 2025).

However, SWOT faces notable limitations in contemporary environments. Designed for stable conditions, it lacks the quantitative depth needed to address modern uncertainty (Zhao, 2024). Critics point to its subjectivity and the difficulty of linking SWOT elements to actionable strategies (Zhao, 2024). To overcome these issues, especially in fast-evolving IT sectors, scholars propose

Fuzzy SWOT, which incorporates expert judgment and membership functions to better manage ambiguity (Zhao, 2024).

Porter's Five Forces remains a widely used tool for analyzing competitive pressures through five dimensions: industry rivalry, threat of new entrants, supplier power, buyer power, and threat of substitutes (Zhao, 2024). It helps firms identify positions within an industry that are less vulnerable to competitive threats by understanding the underlying drivers of profitability (Zhao, 2024). The model also offers a comprehensive view of the external environment beyond simple market share comparisons (Pangarkar and Prabhudesai, 2024).

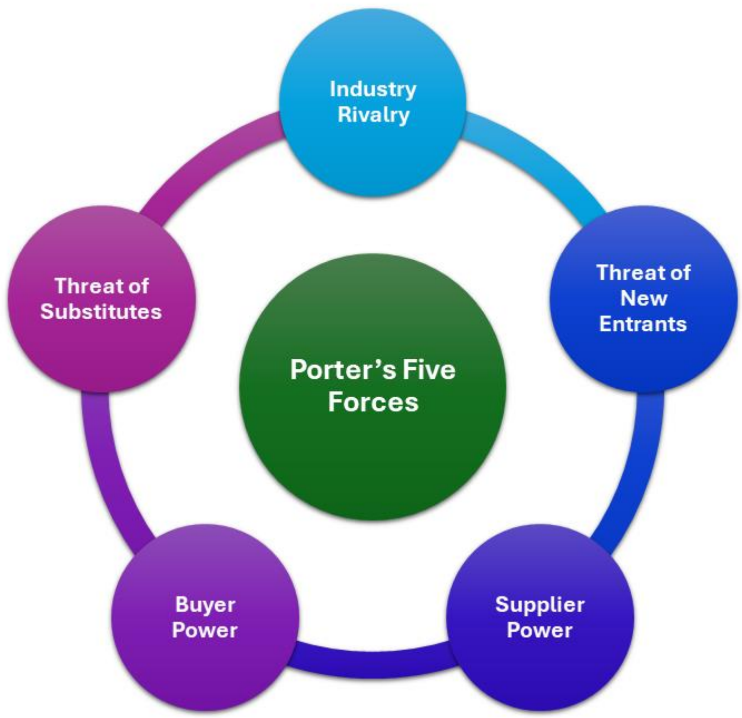

Figure 6. Porter's Five Forces Model. *This framework analyzes the five competitive forces (industry rivals, supplier power, buyer power, threat of new entrants, and threat of substitutes) that collectively determine the profitability and attractiveness of an industry.* ***Source:*** *Author's own creation, based on Porter (1979).*

Yet, the model faces challenges in the digital era. Industry boundaries have become increasingly fluid, illustrated by companies like Amazon operating simultaneously in retail and technology, making traditional industry classifications less meaningful (Cuthbertson and Furseth, 2022). The model is also criticized for being overly static and for overlooking innovation and cooperative strategies, such as ecosystem-based competitions, which expands total value rather than merely redistribute it (Nonaka and Takeuchi, 2021). Additionally, Porter's "outside-in" logic is said to suffer from resource myopia, underestimating the importance of internal capabilities and dynamic adaptation in responding to technological disruption (Nonaka and Takeuchi, 2021). As a result, scholars recommend shifting from broad industry-level analysis to more focused segment-level assessments that consider specific drivers, such as demand for advanced features (Pangarkar and Prabhudesai, 2024).

Overall, contemporary research agrees that no single strategic tool is sufficient. Instead, firms should combine traditional frameworks with digital, data-driven approaches such as AI and Big Data analytics (Zhylinska and Gitko, 2025). Integrating these methods enhances decision-making speed and supports sustainable competitive advantage in an increasingly global and dynamic environment (Jowarder and Jowarder, 2025).

2.6 The Role of Innovation in Sustaining Competitive Advantage

Innovation serves as the central mechanism enabling organizations to convert static assets into dynamic performance capabilities. While historical strategies, particularly RBV prioritized the control of finite resources, contemporary theory argues that in fast-paced digital environments, assets such as algorithms and data suffer from value decay unless they are continuously refreshed through innovation (Cuthbertson and Furseth, 2022). As a result, the scope of innovation has expanded beyond simple product development to necessitate comprehensive strategic models that synthesize technology, ecosystem dynamics, and human capital.

The classic RBV argues that firms gain competitive advantage by owning resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Nasifoglu Elidemir et al., 2020). In the digital era, however, the nature of such resources has changed. Unlike physical assets such as land and minerals, digital assets (particularly data and algorithms) depreciate quickly (Cuthbertson and Furseth, 2022). Customer data is only useful when it is up to date, and algorithmic advantages last only until a competitor develops a better model (Cuthbertson and Furseth, 2022)..

Because digital resources are easily transferable and replaceable, they provide only a temporary or “retainable” advantage that must be continuously renewed. As a result, long-term competitiveness now depends on a firm’s ability to constantly innovate and refresh these digital assets rather than merely owning them (Cuthbertson and Furseth, 2022). Across industries innovation is increasingly viewed not just as a growth mechanism but as essential for survival amid intense competition and shifting customer expectations (Kuncoro and Suriani, 2018; Nasifoglu Elidemir et al., 2020).

Innovation theory has expanded from focusing solely on products to encompassing Business Model Innovation (BMI), which involves redesigning how value is created, delivered, and captured (Jorzik et al., 2024). AI accelerates this shift by pushing firms to rethink and restructure their business models (Kanbach et al., 2024; Reim et al., 2020). For example, AI enables "servitization", where manufacturers transition from selling products to selling outcomes, such as performance-based service contracts, which fundamentally alters revenue models (Ghosh, 2025).

Innovation is also steering firms toward circular economy models. AI capabilities, especially perceptive, predictive, and prescriptive analytics, help extend product lifecycles and optimize resource use, generating both economic and environmental benefits (Sjödin et al., 2023). In addition, firms are increasingly adopting "Orchestrator models", where value is co-created through networks and ecosystems rather than through traditional vertical integration. This shift requires strategic management of partners and digital platforms (Sjödin et al., 2023).

To maintain competitive advantage through innovation, firms are turning to strategic frameworks designed for volatile environments. One key requirement is Strategic Ambidexterity, which is the ability to balance efficiency in current operations (exploitation) with experimentation and exploration of new opportunities (exploration) (Doz, 2020). In the AI context, this becomes "AI Embidexterity", where organizations use AI both to optimize existing processes and to discover new business possibilities (Perifanis and Kitsios, 2023). Achieving this balance requires strategic agility, which includes environmental sensitivity, flexible resource allocation, and rapid collective decision-making (Doz, 2020).

Innovation strategies also differ in how they engage with the market. Market-Driven firms respond to customer needs, while Market-Driving firms proactively shape and educate the market (Kuncoro and Suriani, 2018). Market-driving strategies can reshape industry structure and limit competitor's opportunities, thereby strengthening long-term competitive advantage (Kuncoro and Suriani, 2018).

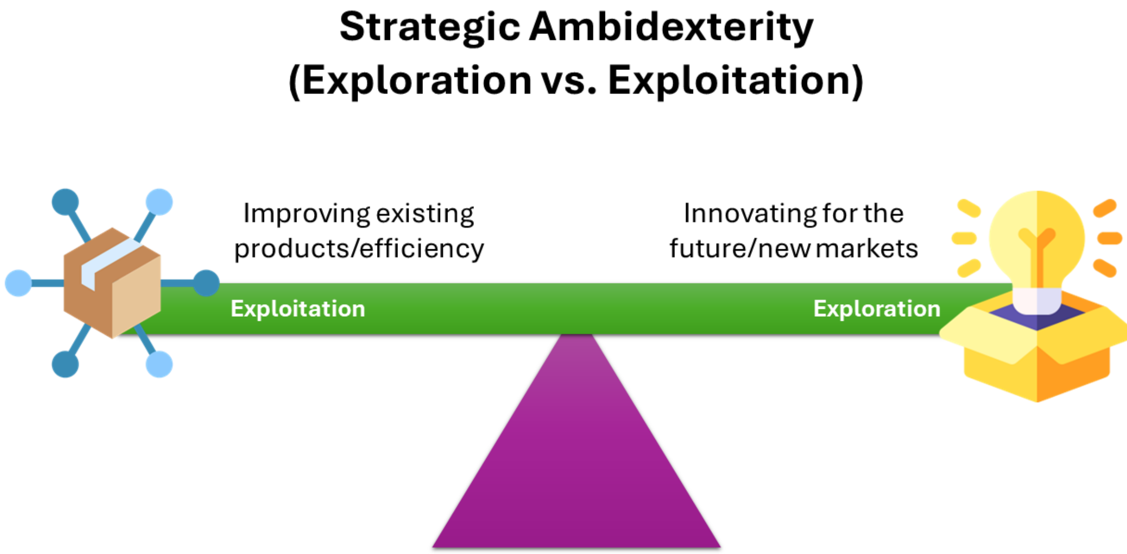

Figure 7. Strategic Ambidexterity. *This diagram illustrates the organizational paradox of balancing Exploitation, which is the refinement of existing competencies and efficiencies, with Exploration, which is the pursuit of new opportunities and innovations, to secure long-term competitiveness.* ***Source:*** *Personal editing using icons from Freepik, and herikus via the Flaticon platform; based on March (1991).*

In contrast to Porter's external "outside-in" perspective, the Inside-Out and Human-Centric Strategy begins with the values, aspirations, and insights of founders and employees (Nonaka and Takeuchi, 2021). This approach emphasizes human judgment, tacit knowledge, and "practical wisdom" (phronesis) as the foundation of strategy, rather than relying solely on data analytics (Nonaka and Takeuchi, 2021). High-Performance Work Practices (HPWPs) further support innovation by motivating employee creativity; because these behaviors are socially complex, they are difficult for competitors to imitate and thus form a strong basis for competitive advantage (Nasifoglu Elidemir et al., 2020).

Technological innovation is widely recognized as a major driver of sustainable competitiveness across industries (Hamdouna and Khmelyarchuk, 2025). Generative AI expands opportunities for BMI by making knowledge more accessible and reducing the cost of producing content, thereby lowering barriers to entry (Kanbach et al., 2024). In B2B settings, the ability to detect market trends and act on them through marketing analytics represents a dynamic capability that supports long-term advantage (Hossain et al., 2022). Sustainable AI advantage also depends on reinforcing feedback loops: better outcomes generate more data, which improves algorithms, creating a self-strengthening cycle that is difficult for competitors to replicate (Mishra and Tripathi, 2021) (Dzreke, 2024; Mishra and Tripathi, 2021).

To effectively connect innovation with sustainable competitive advantage, firms must adopt a comprehensive approach. This begins with re-institutionalization, where organizational culture and processes are redesigned to integrate human expertise with AI systems, recognizing employees as central contributors to value creation rather than cost factors (Chowdhury et al., 2024). It also requires ongoing reconfiguration, as firms develop capabilities to continuously update and optimize their offering in response to technological change (Sjödin et al., 2023). Ultimately, innovation must align with the Triple Bottom Line (economic, environmental, and social goals), since sustainable technological advancements are becoming essential for long-term competitiveness (Hamdouna and Khmelyarchuk, 2025).

In summary, the contemporary competitive landscape demands that firms move beyond static resource ownership and embrace continuous renewal through innovation, dynamic capabilities, and human-centered strategic thinking. As digital assets become increasingly perishable and easily replicated, sustainable advantages emerge not from procession but from the capacity to adapt, reconfigure, and co-evolve with technological and market shifts. AI-enabled business model innovation, strategic ambidexterity, and high-performance work practices collectively form the foundation of this new paradigm, where human insight and technological intelligence operate in tandem. Ultimately, organizations that integrate innovation with long-term economic, environmental, and social objectives are best positioned to thrive in an era defined by rapid change and relentless competition.

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Chapter 3
Technological Advancements: Defining the AI Ecosystem

3.1 Data Science and Big Data Analysis

The contemporary strategic landscape is increasingly defined by a firm's ability to navigate the "fourth science paradigm", which is characterized by data - intensive scientific discovery (Cao, 2018; Elshawi et al., 2018). At the core of this shift lies Data Science, an interdisciplinary field that synthesizes statistics, computing and management to transform raw information into organisational value (Cao, 2018). While traditional data analysis often focuses on retrospective reporting, modern Data Science serves as a comprehensive system designed to extract actionable insights from an increasingly complex and high - velocity digital environment (Elshawi et al., 2018).

To understand the strategic importance of these fields, the relationship between Big Data and Data Science can be viewed as analogous to that of a refinery: Big Data serves as the "crude oil" or the raw strategic asset, while Data Science provides the specialized techniques and machinery required to refine that asset into usable product (Elshawi et al., 2018). Specifically, Big Data Analytics involves the theories and technologies used to uncover hidden patterns and correlations within datasets that are too massive or intricate for conventional tools to handle (Cao, 2018; Nageye et al., 2024). This systematic processing is what enables evidence-based decision making in high stakes environments, where intuition alone is insufficient (Nageye et al., 2024).

The transition into the Artificial Intelligence (AI) era has necessitated an expansion of how data is categorized, moving from the foundational "3 Vs" to a broader "Spectrum of Vs". This framework addresses modern complexities such as the sheer scale of information **(Volume**), the real time speed of generation (**Velocity**) and the diversity formats ranging from structured tables to unstructured text and video (**Variety**) (Amin et al., 2022; Kumar et al., 2024). Beyond these logistical challenges, managers must also account for the truthfulness and relevance of data (**Veracity and Validity**), as poor quality leads to skewed models (Kumar et al., 2024). Furthermore, the unpredictability of data patterns (**Volatility and Variability**) and the inherent security risks (**Vulnerability**) must be balanced against the ultimate goal of deriving actionable insights (**Value**) and communicating them clearly to stakeholders through accessible formats (**Visualization**) (Elshawi et al., 2018; Kumar et al., 2024).

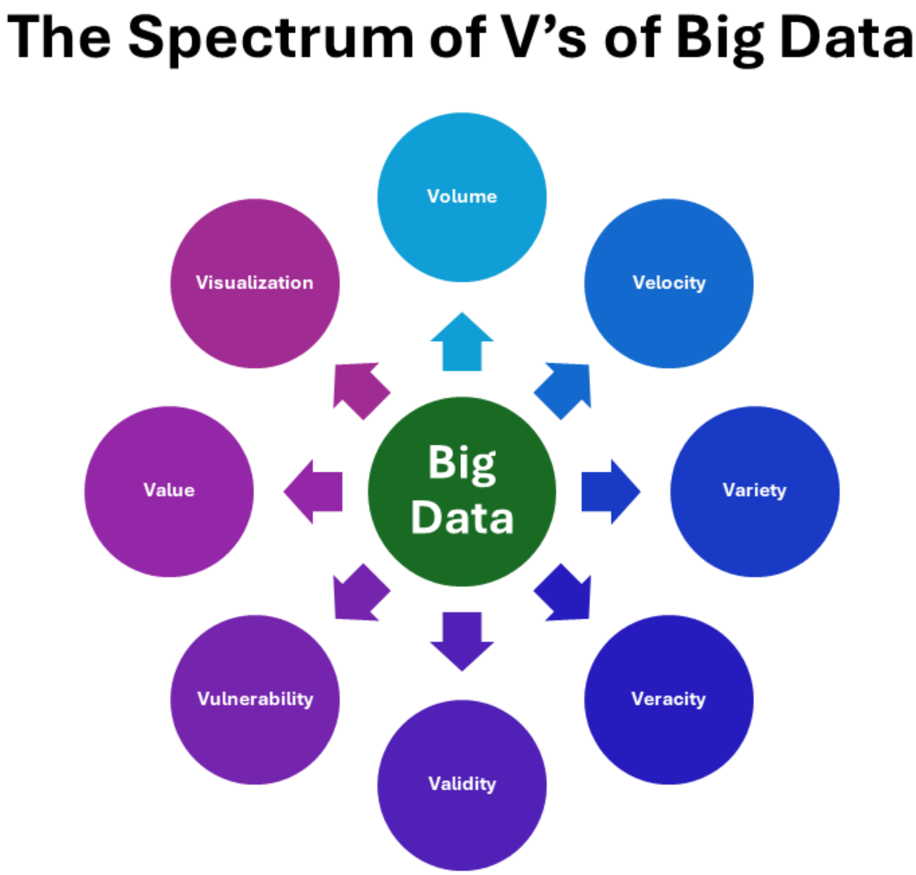

Figure 8. The Expanded Spectrum of V's of Big Data. *This framework illustrates the multi-dimensional nature of data as a strategic resource, moving from technical characteristics (Volume, Velocity, Variety) to qualitative and strategic dimensions (Veracity, Validity, Vulnerability, Value and Visualization) required for effective AI integration.* ***Source:*** *Author's own creation, based on Laney (2001) and Kumar (2024).*

The strategic utility of this data ecosystem is best illustrated through the evolution of the analytics spectrum, which moves from simple hindsight to complex foresight (Cao, 2018). Descriptive and diagnostic analytics answer "what happened" and "why", providing a baseline for performance through dashboards and historical reporting (Cao, 2018; Kumar et al., 2024; Riahi et al., 2021). However, to gain a competitive edge, firms must move toward predictive analytics, which utilizes statistical models and Machine Learning (ML) to forecast future behaviours and address the problem of "unknown unknowns" (Cao, 2018; Sarker, 2021). The most advanced stage, prescriptive analytics, goes a step further by using optimization and simulation to recommend the "next best action" to achieve a desired organizational outcome (Cao, 2018; Riahi et al., 2021).

The engines driving these analytical stages are Machine Learning (ML) and its specialised subset, Deep Learning (DL). ML allows computers to learn from data without explicit programming, utilizing supervised and unsupervised methods to predict values or identify hidden structures (Janiesch et al., 2021; Sarker, 2021). More complex scenarios may require semi - supervised learning or reinforcement learning, where an agent optimizes a strategy through environmental feedback (Enholm et al., 2022; Sarker, 2021). Deep Learning, based on Artificial Neural Networks (ANN), provides the capability to process high - dimensional, unstructured data, such as images via Convolutional Neural Networks (CNNs) or sequential text and time - series data via Recurrent Neural Networks (RNNs) (Jackson et al., 2024; Janiesch et al., 2021; Nageye et al., 2024; Oliveira et al., 2024).

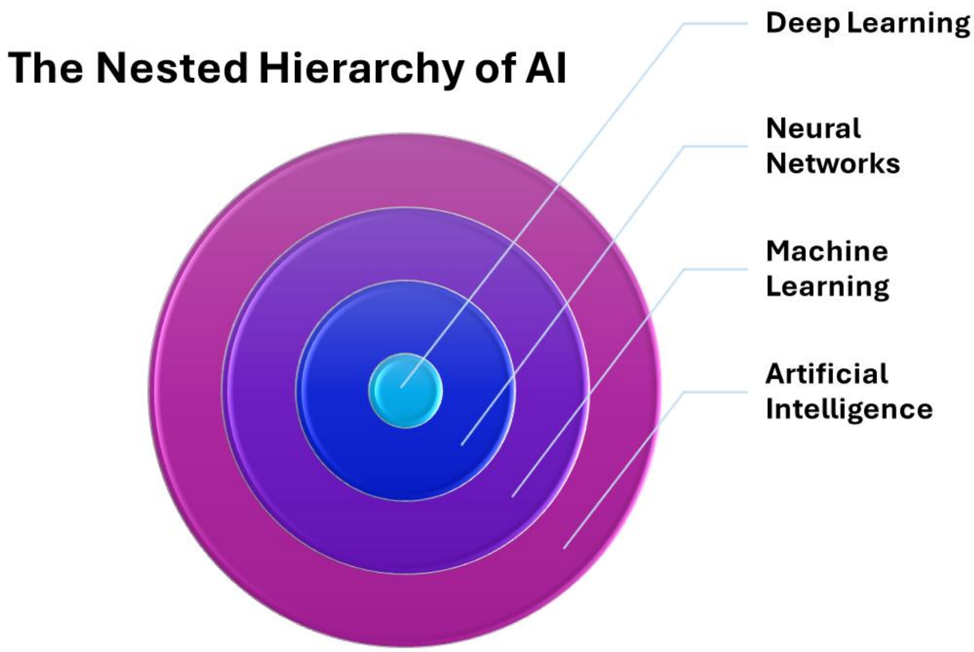

Figure 9. The Nested Hierarchy of AI. *This diagram clarifies the relationship within the field of intelligence, illustrating how Artificial Intelligence encompasses Machine Learning, which in turn contains Neural Networks and Deep Learning.* ***Source:*** *Author's own creation, based on Frazier and Song (2024).*

Integrating these technologies into a firm's strategy is a critical component of the Resource Based View (RBV) and the development of Dynamic Capabilities. Unlike traditional physical assets, the value of data and algorithms decays over time, meaning that possession of data is not a sufficient source of advantage (Cuthbertson and Furseth, 2022). Instead, a sustainable competitive advantage is derived from the dynamic capability to continuously renew, analyse, and reconfigure these data resources (Cuthbertson and Furseth, 2022). This is evident in Marketing Analytics

Capability (MAC), which allows firms to sense and seize market trends more effectively (Hossain et al., 2022), and in Generative AI (GenAI), which adds a creative dimension to standard AI by generating novel scenarios or synthetic data where real world information is scarce (Jackson et al., 2024).

Despite the potential, several significant hurdles remain that can undermine strategic goals. The principle of “garbage in, garbage out” remains a primary concern, as inaccurate data leads to flawed models (Patil, 2025). Additionally, the “black box” nature of deep learning models often lacks the explainability required in regulated industries, creating a barrier to full adoption (Hossain et al., 2022). Finally, the successful implementation of these systems is often limited by technical bottlenecks in merging operational and information technology, as well as a persistent talent gap which is the shortage of professionals who possess the rare blend of statistical, coding and business acumen (Cao, 2018; Ghosh, 2025).

3.2 Internet of Things (IoT) and Smart Systems

The Internet of Things (IoT) has undergone a significant transformation, evolving from a simple network of connected computers into a massive ecosystem of “Smart Objects” capable of sensing, communicating and interacting with the physical environment (Gupta and Gupta, 2016; Oliveira et al., 2024). In the context of strategic management, these devices serve as the “sensory nervous system” of the organization, providing the essential data fuel required to power AI engines. This technological convergence is increasingly categorized in literature as the Internet of Intelligent Things (IoIT) or Cyber - Physical Systems (CPS).

The strategic value of IoT is primarily found in its architectural role as the foundational “Perception Layer”. Embedded with sensors and specialized software, these physical objects overcome human perceptual limitations by continuously gathering data from environments that are otherwise difficult or dangerous to monitor (Gupta and Gupta, 2016; Oliveira et al., 2024).This data pipeline is characterized by immense Volume and Velocity, with projections suggesting a global data generation scale of 163 zettabytes by 2025 (Amin et al., 2022). Crucially, the literature emphasizes a symbiotic relationship between these technologies: without AI, the massive streams of data generated by IoT remain incomprehensible to human analysts and therefore useless; conversely, without IoT, AI lacks a direct, real time connection to the physical world (Ghosh, 2025).

The hardware facilitating this data collection is generally categorized by its computational capacity. Low - end “TinyML” microcontrollers (such as Arduino or ESP32) are utilized for energy - efficient monitoring of simple scalar data like temperature or vibration (Oliveira et al., 2024). In contrast, high - end edge devices and single - board computers, such as NVIDIA Jetson, possess the power to act as sensor gateways that process complex visual or auditory data before it is transmitted to the cloud (Oliveira et al., 2024). These devices are further enabled by bridging technologies such as Radio Frequency Identification (RFID) and Near Field Communication (NFC), which allow for the seamless identification and tracking of physical assets in a virtual environment (Gupta and Gupta, 2016).

This integration grants AI systems specific functional capacities that are vital for strategic advantage. First, the perspective capacity allows for real - time monitoring of operational environments, creating "perspective maps” of machine health or infrastructure (Sjödin et al., 2023). In manufacturing, this allows for in - situ monitoring where thermal or optical sensors detect defects layer by layer during production (Elahi et al., 2023). Second, the predictive capacity of AI is fueled by IoT’s pattern recognition, allowing firms to shift from reactive to proactive strategies, such as predictive maintenance or demand forecasting (Mohammed et al., 2025). Finally, the prescriptive capacity involves the use of Digital Twins which is virtual replicas fed by real - time IoT data, which allow AI to simulate scenarios and automatically optimize resources in sectors like smart grids or mining without human intervention (Elahi et al., 2023; Sjödin et al., 2023).

A pivotal advancement in this field is the shift toward Edge Computing or moving the “brain” closer to the “senses”. By deploying AI models directly onto the IoT device at the edge of the network, firms can significantly reduce latency and bandwidth consumption (Morandini et al., 2023). This local inference ensures that only the relevant insights of anomalies are transmitted to central systems, making data collection more efficient and secure (Ghosh, 2025; Oliveira et al., 2024). This loop is already transformative across various sectors, from the Internet of Medical Things (IoMT) providing early warning scores for patient health to “smart supply chains” that use real - time tracking for route optimization and risk management (Patil, 2025; Rashid and Kausik, 2024).

However, relying on IoT as a strategic data layer introduces several challenges. The integrity of AI outputs depends entirely on data veracity; noisy or inaccurate sensor data leads to flawed models, making resource - intensive data cleaning a necessity (Amin et al., 2022; Reim et al., 2020). Furthermore, the proliferation of connected devices increases the “attack surface” for security threats, such as False Data Injection, where malicious actors compromise sensors to feed erroneous information to AI Systems (Ghosh, 2025). Finally, organisations must navigate technical bottlenecks related to the interoperability of devices from different manufacturers and the energy constraints of running complex AI models on battery - powered hardware (Ghosh et al., 2018; Oliveira et al., 2024).

3.3 Machine Learning (ML) and Deep Learning (DL) Drivers

In today’s technological environment, the Internet of Things (IoT) has progressed from basic device interconnectivity toward what is now described as the IoIT or Cyber - Physical Systems (CPS). Within this framework, IoT devices operate as a distributed sensory network that supplies data to the cognitive core of AI (Oliveira et al., 2024). From a strategic standpoint, these technological drivers function not only as operational enablers, but as essential resources that support the dynamic capabilities of sensing, seizing and transforming (Jackson et al., 2024).

At the foundation of this architecture lies the Perception Layer, where sophisticated sensors and actuators convert physical phenomena into digital information. By enabling AI - driven perception, such as visual recognition through computer vision or auditory interpretation through audio analytics, these technologies extend human capabilities and allow continuous monitoring of critical environments (Gupta and Gupta, 2016; Jackson et al., 2024). This contributes to a state of “Digital Awareness", enabling organisations to identify early indicators of market changes or operational disruptions, including predictive maintenance signals, ahead of competitors (Ghosh et al., 2018; Ghosh, 2025). Moreover, these devices generate the high - quality Big Data necessary for training ML models, reducing the risk of poor model performance caused by low - quality inputs (Amin et al., 2022; Kumar et al., 2024).

As computation increasingly shifts from centralized cloud infrastructures to edge environments, the Processing Layer and the emergence of TinyML have introduced new forms of strategic responsiveness. Executing machine learning models directly on low - power microcontrollers enables real - time decision making with minimal latency (Oliveira et al., 2024). This capability is essential in time sensitive domains such as autonomous mobility or emergency medical interventions, where even milliseconds matter (Amin et al., 2022). Additionally, local processing strengthens privacy and security by reducing the need to transmit sensitive data, addressing vulnerabilities associated with large scale data flows while supporting sustainability objectives aligned with “Green AI” (Kumar et al., 2024; Oliveira et al., 2024).

The value of IoT systems is further shaped by the Connectivity Layer, which relies on technologies such as 5G, LoRaWAN and Bluetooth Low Energy (BLE). In particular, 5G significantly enhances AI’s interaction capabilities by enabling high - speed, low - latency control of remote operations, including applications like telesurgery (Jackson et al., 2024). This connectivity transforms isolated devices into an integrated ecosystem characterized by “swarm intelligence”, where distributed nodes collaborate to address complex challenges (Amin et al., 2022; Elahi et al., 2023).

At the Intelligence Layer, ML and DL serve as the system’s cognitive mechanisms. Unlike traditional software, ML enables systems to identify patterns and improve performance without explicit programming (Enholm et al., 2022; Ghosh et al., 2018). Deep Learning, based on ANN, is particularly effective for processing unstructured data such as images and speech, while the emergence of GenAI introduces a new dimension of computational creativity (Janiesch et al., 2021). Strategically, GenAI can support scenario generation for stress - testing or producing synthetic datasets to enhance model training in contexts with limited real - world data (Jackson et al., 2024). These capabilities enable organizations to progress from descriptive analytics toward predictive and prescriptive insights, directly contributing to resource optimization and strategic reconfiguration (Jowarder and Jowarder, 2025; Mohammed et al., 2025).

Finally, the Simulation and Trust Layers establish the conditions for reliable strategic implementation. Digital Twins, which are virtual models of physical assets or systems, enable “virtual prototyping”, allowing decision makers to evaluate strategies and optimize resource deployment in a risk - free digital environment before real world execution (Elahi et al., 2023; Ghosh et al., 2018). To ensure the reliability of the data that informs these simulations, Blockchain functions as a Trust Layer by providing an immutable and transparent ledger that safeguards data integrity (Amin et al., 2022). This prevents malicious data manipulation, such as “False Data Injection”, and supports trustless collaboration across supply chain networks (Mohammed et al., 2025). Achieving sustained competitive advantage requires the coordinated integration of these layers: IoT acts as the sensory system, 5G as the communication network, AI as the analytical core and Digital Twins as the strategic simulation environment (Ghosh et al., 2018).

The IoT Three-Layer Architecture

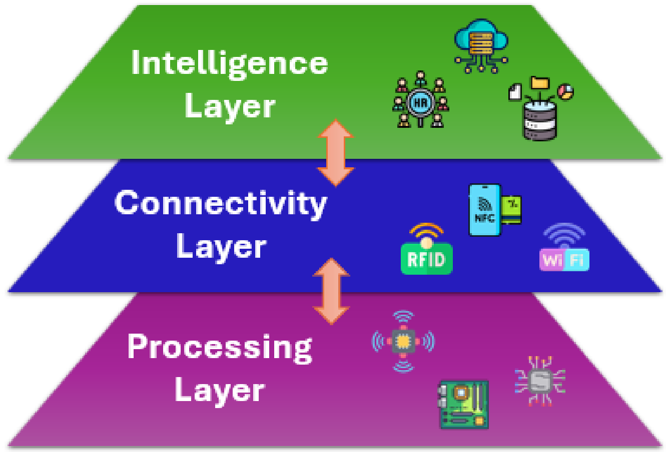

Figure 10. The IoT Three-Layer Architecture. *This diagram illustrates the functional flow from the Processing Layer (Sensing and Data Acquisition), through the Connectivity Layer (Transmission and Connectivity) to the Intelligence Layer, where data is processed by AI systems to generate business value.* ***Source:*** *Personal editing using icons from Freepik, kerismaker, Iconjam, surang, Eucalyp, Flat Icons, and RaftelDesign via the Flaticon platform; based on Al-Zoubi et al. (2023).*

3.4 Defining Artificial Intelligence (AI) for Strategic Management

Within strategic management, AI is increasingly conceptualized not simply as software or algorithms, but as a fundamental organizational capability. For the purposes of this thesis, AI is defined in a non - technical and strategically oriented manner as a system's ability to accurately interpret external data, learn from it and apply the resulting insights to achieve defined objectives through adaptive behaviour (Sjödin et al., 2023). In organizational settings, AI operates as a data - driven ecosystem that enhances human capabilities by sensing, understanding, learning and acting, thereby enabling faster and more accurate decision making (Jaiswal et al., 2022).

Earlier definitions of AI emphasized enabling machines to perform tasks that traditionally required human intelligence (Gao et al., 2024; Stone et al., 2024). Contemporary management scholarship, however, has shifted toward a more pragmatic interpretation focused on replicating human rationality rather than human consciousness. Under this perspective, AI is defined by its capacity for rational action, evaluating alternatives and selecting the option most likely to achieve a specific goal, independent of human - like awareness (Riahi et al., 2021). Strategically, this positions AI as a hybrid between capital and labour: it resembles labour through its ability to learn and improve autonomously, yet maintains the scalability and replicability of capital (Reim et al., 2020). This distinction is essential when examining the balance between automation, which replaces human tasks, and augmentation, which enhances human judgment and strengthens strategic decision quality (Enholm et al., 2022).

To integrate AI effectively into strategic practice, it is more useful to conceptualize the technology in terms of its functional capabilities rather than its technical architecture. Existing frameworks highlight several core capabilities that organizations leverage to create value. Learning and perception form the foundation, enabling systems to extract knowledge from data patterns and interpret the environment through text, image and audio analysis (Jackson et al., 2024; Stone et al., 2024; Xu et al., 2021). These are complemented by prediction and reasoning, which support forecasting future outcomes and solving complex problems such as logistics planning (Jackson et al., 2024). Interaction and adaptation further allow AI systems to communicate with humans or other technologies and to adjust their performance as conditions evolve (Jackson et al., 2024). More recently, creativity (enabled by GenAI) has emerged as an additional capability, allowing systems to produce new content, scenarios or strategic options, distinguishing generative models from earlier analytical forms of AI (Dzreke, 2024).

For strategic clarity, it is important to specify the type of AI being examined. The literature consistently distinguishes three categories: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI) (Rashid and Kausik, 2024; Riahi et al., 2021). While AGI and ASI remain theoretical or speculative, current business applications operate exclusively within ANI, where systems excel at highly specialized tasks such as fraud detection or demand forecasting within predefined boundaries (Riahi et al., 2021). From an RBV perspective, AI is best understood as a composite organizational capability rather than a standalone resource. This capability reflects the firm's proficiency in selecting, integrating and deploying technical assets, such as data and algorithms, together with human expertise and intangible resources like culture and change management (Peretz-Andersson et al., 2024). Because AI systems rely fundamentally on Big Data to function, any strategic definition of AI implicitly includes the underlying data infrastructure required to support learning and action (Goralski and Tan, 2020; Kumar et al., 2024).

3.5 The Generative AI Landscape

Generative Artificial Intelligence (GenAI) marks a significant departure from traditional analytical AI by shifting the focus from classification to creation. Whereas conventional discriminative models analyse existing data to make predictions, GenAI, which is enabled by foundation models and Large Language Models (LLMs), produces new content such as text, images, code and synthetic datasets that emulate human reasoning and creativity. This development introduces a new organizational capability: artificial creativity. GenAI's performance is driven by advanced architectures including Transformers, Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), which rely on attention mechanisms to capture complex data relationships and adversarial training to enhance output realism (Gao et al., 2024; Jackson et al., 2024; Oliveira et al., 2024).

From a strategic perspective, GenAI enables the industrialization of cognitive processes, particularly through synthetic data generation. This capability addresses the "cold start" challenge by allowing firms to train models even when real - world data is limited, sensitive or costly to obtain, thereby creating a competitive edge (Jackson et al., 2024; Janiesch et al., 2021). GenAI also accelerates business model innovation by reducing the marginal cost of expertise and content creation to near zero (Kanbach et al., 2024). By narrowing the productivity gap between novice and expert workers, GenAI democratizes access to specialized knowledge. This effect is particularly evident in fields such as law and software development, where tools like GitHub Copilot shift professional activity from content generation to content validation, significantly increasing throughput (Jackson et al., 2024; Kanbach et al., 2024).

This technological transformation reshapes work design and Strategic Human Resource Management (SHRM). Human roles increasingly evolve from "creators" to "editors" or "curators", where value is derived from evaluating and refining AI - generated outputs (Kanbach et al., 2024). Although concerns about job displacement persist, the dominant strategic narrative emphasizes augmentation: Gen AI reduces the burden of repetitive cognitive tasks, enabling employees to focus on higher level analytical and creative work (Chowdhury et al., 2024). As a result, HR functions must adopt the role of institutional entrepreneurs, redesigning workflows to support human - AI collaboration while deploying personalized AI - driven training and recruitment systems and managing risks such as algorithmic bias (Chowdhury et al., 2024; Huang et al., 2023).

Operationally, LLMs serve as essential interfaces between human intent and complex technical infrastructures. Methods such as Retrieval - Augmented Generation (RAG) allow managers to query unstructured data using natural language, thereby bridging the gap between technical systems and executive decision - making (Kumar et al., 2024). This capability accelerates the development of digital twins, logistics simulations and automated coding and even supports automated negotiation processes in procurement (Jackson et al., 2024). However, these advantages are accompanied by governance challenges, including hallucinations, instances where models generate inaccurate information, and the broader “black box” problem, where limited explainability undermines trust in high - stakes environments (Chowdhury et al., 2024; Rashid and Kausik, 2024; Saranya and Subhashini, 2023).

A final strategic consideration concerns the choice between adopting off the shelf GenAI models or customizing foundation models with proprietary data. While pre - trained models offer rapid deployment, customized models provide a more defensible competitive advantage by combining LLM reasoning capabilities with unique, VRIO organizational data (Dzreke, 2024; Kanbach et al., 2024). To avoid strategic convergence, where firms relying on identical base models arrive at similar decisions, organizations must invest in proprietary data pipelines and cultivate organizational agility (Wang et al., 2025). Ultimately, sustainable advantage in the GenAI era stems not from the models themselves, which are rapidly commoditizing, but from the governance structures, data ecosystems and workflow integrations that determine how effectively these models are deployed (Dzreke, 2024; Gao et al., 2024; Jackson et al., 2024)

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Chapter 4
Strategic Human Resource Management and Competitive Advantage

4.1 Human Capital as a Strategic Resource (RBV Perspective)

Understanding the role of human resources in the digital era begins with the Resource-Based View (RBV), which argues that human capital is not simply an operational cost but a strategic asset made up of individuals' knowledge, skills, creativity, health, and values (Pasban and Nojedeh, 2016). Unlike physical or financial resources, human capital is inseparable from the people who hold it, making it inherently unique (Pasban and Nojedeh, 2016). For human capital to create Sustainable Competitive Advantage (SCA), it must meet the VRIO criteria, as mentioned before, which are Valuable, Rare, Inimitable and supported by Organizational systems that enable its full utilization (Kero and Bogale, 2023). This means human capital must help the firm exploit opportunities or counter threats (Kuncoro and Suriani, 2018), be scarce in the labour market (Anastasiu et al., 2020), be difficult for competitors to imitate due to social complexity or causal ambiguity (Anastasiu et al., 2020; Huang et al., 2023), and be supported by effective Strategic HRM systems (Hamadamin and Atan, 2019).

A central debate in RBV research concerns which type of human capital provides the strongest advantage. Traditionally, scholars argued that general human capital, which are skills applicable across many firms, cannot sustain competitive advantage because it is mobile and easily poached (Lanza and Simone, 2025). This led to the view that firms should invest primarily in firm-specific human capital, which is harder for competitors to replicate (Lanza and Simone, 2025). However, recent studies challenge this assumption, showing that mobile and general skills can also strengthen competitiveness. In high-turnover industries, newcomers with diverse backgrounds enhance a firm's absorptive capacity, which is the ability to identify and integrate external knowledge (Lanza and Simone, 2025). Moreover, employees with strong general skills signal organizational quality, attracting additional high-performing talent and creating a self-reinforcing recruitment advantage (Lanza and Simone, 2025). This produces a complementary dynamic where fresh perspectives from newcomers combine with the deep institutional knowledge of long-term employees (Lanza and Simone, 2025).

Even when individual skills can be hired, the broader human capital system remains difficult to imitate due to isolating mechanisms. Personalized HRM practices create causal ambiguity by making it unclear how specific HR inputs translate into performance outcomes (Huang et al., 2023). Competitive advantage also arises from social complexity (the networks, trust, and relationship among employees) rather than from individual star performers (Hamadamin and Atan, 2019). In digital service firms, long-term advantage depends on "physical dynamic capabilities" such as leadership, culture, and routines that coordinate digital resources; while algorithms can be copied, the human systems that continually update them cannot (Cuthbertson and Furseth, 2022). Additionally, tacit knowledge, which is deeply embedded, experiential expertise, remains non-transferable and socially complex, giving humans an edge in areas where AI still lacks capability (Morandini et al., 2023; Nonaka and Takeuchi, 2021).

AI is also reshaping what counts as "valuable" human capital. As automation increasingly handles routine and analytical tasks, human advantage shifts toward "Evergreen Skills" such as leadership, empathy, advanced communication, and strategic judgement, capabilities that are difficult for AI to replicate(Jaiswal et al., 2022). The worker's role is evolving from creator to editor, where competitive advantage lies in the ability to evaluate, refine, and contextualize AI-generated outputs (Kanbach et al., 2024). Maintaining this advantage requires continuous learning, where the capacity to unlearn outdated knowledge and acquire new skills becomes a core strategic attribute (Morandini et al., 2023).

To protect the strategic value of human capital, firms must also examine external pressures by adapting Porter's Five Forces to the labour market (Anastasiu et al., 2020). This includes competition for scarce talent, the influence of universities and recruiters on labour supply, and the power of employer branding in attracting skilled workers (Anastasiu et al., 2020). Firms must also consider the threat of substitutes, such as AI and robotics replacing routine tasks, and the threat of new entrants, as globalization and migration expand the pool of skilled labour (Anastasiu et al., 2020). Ultimately, human capital is best understood as a dynamic capability rather than a static resource. While digital assets like data and algorithms provide only temporary advantages, human capital offers sustained competitiveness because it enables innovation, resource reconfiguration, and effective navigation of uncertainty (Cuthbertson and Furseth, 2022).

4.2 The Role of Human Resources in Leveraging AI and Data

As organizations confront the demands of the digital era, the Human Resources (HR) function is undergoing a profound transformation, from a primarily administrative role to one of “Institutional Entrepreneurship". In the age of Generative AI (GenAI), HR is responsible for driving “re-institutionalization”, meaning the redesign of organizational structures, processes, and cultural norms to keep pace with rapid technological change (Chowdhury et al., 2024). This shift requires HR to take ownership of Resource Orchestration (RO), which involves not only acquiring AI tools but integrating them with human expertise. In manufacturing small-medium enterprises (SMEs), for instance, HR leads an “empowering people” configuration by defining human responsibilities for detecting AI errors and assigning data-visualization tasks that support managerial decision-making (Peretz-Andersson et al., 2024).

To support this organizational renewal, HR must help firms move away from rigid hierarchies toward “resource fluidity”, where teams are flexible, project-based, and quickly redeployed. This requires decoupling resource ownership from responsibility and fostering “entrepreneurial matrices” that allow frontline employees to access resources dynamically (Doz, 2020). HR must also address the practical reality that AI systems depend heavily on human labor. These systems require “data janitors”, which are skilled workers who clean, curate, and maintain the dataset that AI relies on. Recognizing and rewarding this often-invisible work is essential for ensuring AI reliability and ongoing innovation (Chowdhury et al., 2024).

Inspired by companies such as Netflix and Google, HR is increasingly adopting Personalized HRM, using AI to move beyond standardized practices and tailor HR processes to individual employees. This personalization creates a distinctive competitive advantage by making human capital more difficult for competitors to imitate (Huang et al., 2023). Through AI-driven analysis of employee data, organizations can offer customized career development paths, training opportunities, and benefits packages that align personal aspirations with organizational needs (Huang et al., 2023). Such personalization strengthens Person-Organization Fit and enhances the psychological contract and “affective commitment”, which AI systems can now monitor and predict through behavioural data (Căvescu and Popescu, 2025; Huang et al., 2023). For firms pursuing differentiation strategies, this individualized approach is especially valuable, whereas cost-leadership firms may rely more on standardized automation (Huang et al., 2023).

HR is also leveraging predictive analytics to shift from reactive to proactive workforce management through Early Warning Systems (EWS). Advanced AI models such as XGBoost and Random Forest are trained on both behavioural data and psychological constructs from Equity Theory and Organizational Commitment Theory, enabling HR to detect early signs of disengagement, such as lack of recognition or stalled career progression, before turnover occurs (Căvescu and Popescu, 2025). Unlike traditional annual surveys, AI-enabled sentiment analysis provides real-time insights into employee morale by analysing communication patterns and productivity indicators, allowing timely interventions to prevent burnout (Bhosale et al., 2024; Căvescu and Popescu, 2025). AI is also used to reduce bias in recruitment by standardizing screening processes, though HR must still oversee these systems to prevent the reinforcement of historical biases embedded in training data (Bhosale et al., 2024; Nawaz et al., 2024).

The “AI Job Replacement Theory” suggests that AI will primarily automate mechanical and analytical tasks, while intuitive, interpersonal, and empathetic tasks will remain human-centered (Huang et al., 2023; Jaiswal et al., 2022). As a result, HR must lead a large-scale reskilling effort focused on “Evergreen Skills” such as communication and leadership, which are competencies that AI cannot easily replicate. As AI takes over routine coding and analytical work, human roles increasingly resemble those of “Editors” or “Curators”, requiring judgment, contextual understanding, and critical evaluation (Jaiswal et al., 2022). HR must also cultivate “transversal skills”, including problem-solving and critical thinking, which enable employees to adapt across tasks and bridge the “skill distance” created by rapid technological change (Morandini et al., 2023). Additionally, HR must address the age-related digital divide by designing inclusive training programs that help older employees adopt AI tools and view technology as supportive rather than threatening (Morandini et al., 2023).

Ultimately, HRs has evolved into that of a strategic architect. By deploying AI to enhance accuracy, automate routine processes, and deliver real-time insights (Nawaz et al., 2024), HR contributes directly to sustainable competitive advantage. This is achieved by cultivating a “human-AI symbiosis”, where AI handles analytical complexity while human capital focuses on creativity, empathy, and sophisticated decision-making (Jaiswal et al., 2022).

4.3 Upskilling, Reskilling, and Organizational Learning

The integration of AI into modern workplaces requires a shift from traditional, static training approaches toward dynamic Organizational Learning. Contemporary scholarship increasingly emphasizes augmentation rather than replacement, highlighting a growing “symbiosis” between human and machine capabilities. To maintain competitive advantage, organizations must identify which competencies are becoming obsolete and which remain “evergreen”. This demands that employees progress beyond basic digital literacy to develop stronger “Data Analysis Skills” and an understanding of “Algorithmic Logic”, enabling them to interpret data-driven insights, evaluate how AI systems generate outputs, and safeguard data quality to avoid "garbage in, garbage out” outcomes (Jaiswal et al., 2022).

At the same time, the emergence of GenAI has dramatically reduced the cost of producing content, shifting the human role from “creator” to “editor” or “curator”. As a result, judgment becomes a critical capability, which is the ability to assess the accuracy, relevance, and quality of AI-generated material (Kanbach et al., 2024). As AI increasingly automates mechanical and analytical tasks within the “thinking economy”, human workers must transition toward the “Feeling Economy”, where social and emotional skills become central sources of value because they are socially embedded and difficult for AI to imitate (Jaiswal et al., 2022; Morandini et al., 2023). Consequently, training investments should shift away from routine, rule-based tasks like basic data entry, scheduling, or simple statistical work, as these functions are rapidly being automated (Jaiswal et al., 2022).

Delivering this new form of training requires abandoning one-size-fits-all models in favour of AI-enabled personalization. Drawing on the “Netflix Model” of Personalized HRM, organizations can use recommendation algorithms to suggest tailored learning modules based on an employee’s learning style, career trajectory, and performance data, thereby improving training return of investment (ROI) by focusing on relevant skill gaps (Huang et al., 2023). AI-powered intelligent tutoring systems can further adapt content difficulty and pacing in real time, preventing disengagement among advanced learners and frustration among novices (Stone et al., 2024). These systems can be enhanced through gamification and immersive simulations, such as virtual negotiations or crisis scenarios, that allow employees to practice skills safely while receiving immediate, automated feedback (Stone et al., 2024; Vrontis et al., 2022).

Upskilling is best understood not as an individual responsibility but as an organizational capability, consistent with RO theory, which emphasizes how skilled individuals are combined and leveraged to create value. Organizational learning is strengthened through cross-functional “fusion” teams that pair domain experts with data scientists, enabling reciprocal knowledge exchange through "collaborative governance" (Dzreke, 2024; Peretz-Andersson et al., 2024). To avoid knowledge concentration, firms should establish internal platforms or "AI Academies" that disseminate expertise from central AI teams to subsidiaries and frontline units (Peretz-Andersson et al., 2024). Moreover, hiring "mobile human capital", meaning highly skilled professionals with shorter tenures, can accelerate learning by injecting fresh perspectives and enhancing absorptive capacity, countering the stagnation that may arise among long-tenured staff (Lanza and Simone, 2025).

Leadership development must also evolve to support an AI-augmented workforce. Leaders do not need technical coding skills, but they must cultivate "AI Ambitions" and an "AI Mindset", enabling them to understand AI at multiple levels of abstraction and grasp its strategic implications (Enholm et al., 2022; Jorzik et al., 2024). HR must foster leaders with strong "strategic sensitivity", which can be developed through purposive mobility, such as rotating leaders into peripheral units or diverse cultural contexts, to challenge entrenched assumptions (Doz, 2020). Additionally, leaders must create psychological safety so that experimentation with AI pilot projects is encouraged and failures are treated as learning opportunities rather than performance shortcoming (Perifanis and Kitsios, 2023).

Finally, organizations must address the potential "dark side" of AI integration, particularly the risk of skill decay, where overreliance on AI weakens human competencies such as critical thinking. Training programs must ensure that employees retain the ability to perform essential tasks independently to maintain effective "human-in-the-loop" oversight (Morandini et al., 2023). HR must also mitigate the digital divide by designing inclusive training that prevents older workers or those from non-technical backgrounds from being marginalized (Jaiswal et al., 2022; Morandini et al., 2023). Ultimately, organizations must reinforce the principle that while AI provides inputs, humans remain accountable for decisions and outcomes, ensuring responsible and safe use of AI technologies (Chowdhury et al., 2024). Table 1 summarizes the shift from traditional talent development models to AI-integrated strategies, highlighting how AI reshapes skills, learning delivery and organizational capability.

Table 1. From Traditional to AI-Integrated Talent Strategy

Dimension	Traditional Talent Strategy	AI-Integrated Talent Strategy	Key References
Skill Focus	Job-specific, technical skills tied to fixed roles	Transversa; “evergreen” skills: communication, leadership, emotional intelligence, judgment	(Jaiswal et al., 2022; Morandini et al., 2023)
Learning Approach	One-size-fits-all training programs	AI-personalized learning paths using recommendations algorithms (“Netflix Model”)	(Huang et al., 2023; Stone et al., 2024)
Role of the Worker	Worker as creator/executor of tasks	Worker as “editor/curator” who evaluates and refines AI-generated outputs	(Jaiswal et al., 2022; Kanbach et al., 2024)
Training Delivery	Standardized classroom or static e-learning	Adaptive learning systems, intelligent tutoring gamification, immersive simulations	(Stone et al., 2024; Vrontis et al., 2022)
Skill Development Priority	Routine, rule-based tasks (data entry, basic analytics)	Data literacy, algorithmic logic, critical thinking, “Feeling Economy” skills	(Jaiswal et al., 2022; Morandini et al., 2023)
Organizational Learning Model	Static, periodic training cycles	Continuous, dynamic learning supported by AI-enabled feedback loops	(Dzreke, 2024; Peretz-Andersson et al., 2024)
Talent Mobility	Fixed roles, rigid hierarchies	Fluid, project-based “fusion teams” enabling cross-functional learning	(Doz, 2020; Peretz-Andersson et al., 2024)
Human-AI Interaction	Humans perform tasks independently	Humans collaborate with AI while maintaining human-in-the-loop oversight	(Huang et al., 2023; Perifanis and Kitsios, 2023)
Outcome	Limited adaptability: skills quickly become obsolete	High adaptability: workforce evolves with technological change	(Jaiswal et al., 2022; Lanza and Simone, 2025)

4.4 HR Analytics and AI-Driven Decision Making

HR Analytics and AI-driven decision making have elevated HRM from a traditional administrative function to a strategic contributor. Organizations are increasingly replacing intuition-based judgment with evidence-based practices, using machine learning, natural language processing, and predictive analytics to enhance every stage of the employee lifecycle.

Recruitment represents one of the most advanced areas of AI adoption, dramatically reducing hiring time and cost while broadening access to talent. Unlike conventional recruitment methods that rely on active applicants, AI systems proactively search internal databases, social media, and online platforms to identify “passive” candidates who may not be actively job-seeking but match organizational needs (Stone et al., 2024). Modern AI tools rely on Semantic Analysis rather than simple keyword matching, enabling them to interpret meaning, such as recognizing “leadership” and “supervision” as equivalent, and thereby improving screening accuracy and reducing hiring time by up to 90% (Stone et al., 2024). AI-powered chatbots further streamline early-stage interactions by answering candidate questions and scheduling interviews, addressing the communication gaps that often frustrate candidates (Nawaz et al., 2024; Stone et al., 2024). Some organizations also employ emotion-sensing technologies and computer vision during video interviews to analyse micro-expressions, vocal tone, and linguistic patterns, inferring traits such as sociability or stress to predict job fit (Stone et al., 2024; Vrontis et al., 2022). Although AI can be programmed to ignore demographic attributes to reduce bias (Stone et al., 2024), scholars caution that biased historical data may still cause algorithms to reproduce discriminatory patterns (Enholm et al., 2022).

One of the most strategic uses of AI in HR is the transition from reactive turnover analysis to proactive attrition prediction. HR departments now employ supervised ML models, including XGBoost, Random Forest, and Logistic Regression, to identify employees at high risk of leaving (Căvescu and Popescu, 2025). These Early Warning systems (EWS) analyse variables such as overtime, promotion history, income, and commute distance to detect “flight risks”, with Random Forest models proving particularly effective at capturing complex, non-linear relationships (Căvescu and Popescu, 2025). Recent studies connect these models to Organizational Commitment Theory, as AI tools increasingly attempt to measure “affective commitment” and “continuance commitment” by monitoring digital behaviour and engagement patterns, enabling HR to intervene with targeted retention strategies before resignations occur (Căvescu and Popescu, 2025).

AI is also reshaping performance management by replacing subjective annual reviews with continuous, data-driven evaluation. Instead of relying on a single yearly assessment, AI systems collect real-time data on productivity, communication patterns, and digital behaviour, allowing managers to provide timely feedback and support (Bhosale et al., 2024; Stone et al., 2024). NLP tools analyse internal communications to assess sentiment and morale, helping identify early signs of burnout or disengagement (Bhosale et al., 2024; Stone et al., 2024). By grounding evaluations in data rather than memory, AI reduces recency bias and favouritism that often distort human appraisals (Stone et al., 2024).

In Learning & Development (L&D), AI enables Personalized HRM by tailoring training and work experiences to individual needs, similar to how Netflix recommends content. AI-driven Learning Management Systems (LMS) act as “virtual coaches”, diagnosing skill gaps and learning preferences to recommend targeted modules while adjusting difficulty and pacing in real time (Huang et al., 2023; Stone et al., 2024). GenAI further enhances L&D by rapidly producing customized training materials, simulations, and assessments, significantly lowering development costs (Chowdhury et al., 2024). AI also supports personalized benefits management by analysing demographic and usage data to recommend tailored “cafeteria-style” benefit packages; for example, childcare support or retirement options (Huang et al., 2023; Stone et al., 2024).

Despite these advancements, AI integration introduces substantial risks that require careful governance. A major concern is the “Black Box” problem: deep learning models often lack transparency, making it difficult to justify decisions such as candidate rejection or promotion denial, which raise ethical and legal concerns (Căvescu and Popescu, 2025; Enholm et al., 2022). There is also the risk of “organizational dehumanization”, where employees feel reduced to data points rather than valued individuals (Khogali and Mekid, 2023). Over-reliance on AI may also lead to “skill decay”, weakening essential HR capabilities such as empathy and intuitive judgment (Morandini et al., 2023). Furthermore, the increasing “datafication” of employees heightens concerns about surveillance and privacy, requiring robust governance frameworks such as General Data Protection Regulation (GDPR) to protect worker rights (Enholm et al., 2022; Vrontis et al., 2022).

4.5 Ethical and Fairness Issues in AI-Enabled HR

The adoption of AI in HRM brings significant ethical and fairness challenges. Although AI can enhance efficiency, it simultaneously introduces risks related to algorithmic bias, privacy violations, and the erosion of human-centred management practices.

A central ethical concern is the potential for systematic bias. AI systems are not inherently objective; they learn from historical data that often reflects existing social inequalities. This "Mirroring Effect" occurs when machine learning models replicate past discriminatory patterns, such as preferring male candidates for technical roles, thereby reinforcing bias rather than eliminating it (Janiesch et al., 2021; Khogali and Mekid, 2023). High-profile cases illustrate this risk. Amazon's AI recruiting tool was abandoned after it learned to downgrade resumes containing the word "women's" having been trained on a decade of male-dominated hiring data (Enholm et al., 2022; Janiesch et al., 2021). Similarly, Google's Vision AI has been criticized for producing racially biased image labels, revealing how training data can embed harmful assumptions (Janiesch et al., 2021).

Bias can also arise from opaque algorithmic correlations. AI-driven hiring tools may filter out qualified candidates based on proxies such as zip codes or employment gaps, which can indirectly reflect race or socioeconomic status (Huang et al., 2023; Stone et al., 2024). Emotion-recognition and facial-analysis technologies used in video interviews raise further concerns. Research shows that micro-expression analysis is often unreliable and may disadvantage individuals from diverse cultural backgrounds or those with disabilities (Stone et al., 2024; Vrontis et al., 2022).

AI's reliance on large volumes of data also contributes to the "datafication" of the workforce, raising serious questions about surveillance, consent, and privacy. Tools such as Electronic Performance Monitoring (EPM), which tracks keystrokes, call duration, or even physical movements through wearables, blur the line between legitimate performance management and intrusive monitoring (Kumar et al., 2024; Vrontis et al., 2022). Such constant observation can heighten stress and create a sense of being surveilled rather than supported (Nawaz et al., 2024; Vrontis et al., 2022). Concerns about informed consent also emerge when organizations collect unstructured data, such as social media activity or internal communications, to predict engagement or turnover, often without employees fully understanding how their data is used (Kumar et al., 2024).

Legal frameworks such as the GDPR and the California Consumer Privacy Act (CCPA) further complicate AI implementation. These regulations require transparency in automated decision-making, giving employees the right to explanations for decisions that significantly affect them (Enholm et al., 2022; Kumar et al., 2024). Centralizing sensitive data, such as health information, performance metrics, or biometric identifiers, also increases the risk of data breaches, which can cause severe reputational and financial harm (Rashid and Kausik, 2024).

Another major ethical challenge is the opacity of advanced AI models. Deep Learning (DL) and Neural Networks often achieve high predictive accuracy but operate as “black boxes”, making it difficult to explain why a particular decision, such as rejecting a candidate, was made (Saranya and Subhashini, 2023). This lack of interpretability complicates accountability, as it becomes unclear whether responsibility lies with the vendor, HR professionals, or data scientists (Jowarder and Jowarder, 2025; Perifanis and Kitsios, 2023). Without Explainable AI (XAI), trust in AI systems diminishes, limiting their acceptance in high-stakes HR decisions (Janiesch et al., 2021).

AI can also reshape the psychological contract between employees and employers. Excessive reliance on algorithms risks "organizational dehumanization”, where workers feel reduced to data points rather than recognized as individuals (Khogali and Mekid, 2023). This can contribute to alienation, burnout, and declining job satisfaction (Khogali and Mekid, 2023). Overdependence on algorithmic recommendations may also weaken human judgment, as managers defer to AI scores instead of applying empathy or contextual understanding (Enholm et al., 2022; Vrontis et al., 2022). Moreover, AI systems often depend on undervalued “data janitors”, meaning workers who clean and label data, raising ethical concerns about invisible labour (Chowdhury et al., 2024).

To mitigate these challenges, scholars advocate for proactive AI Governance rather than reactive compliance. Ethical AI requires maintaining “human-in-the-loop” (HITL) oversight, ensuring that AI supports rather than replaces human decision-making in sensitive areas such as hiring or termination (Huang et al., 2023; Perifanis and Kitsios, 2023). This preserves human empathy and contextual judgement (Huang et al., 2023). Organizations are increasingly adopting ethical frameworks grounded in principles such as Transparency, Fairness, Non-maleficence, and Accountability, including the European Commission's Guidelines for "Trustworthy AI” (Enholm et al., 2022; Perifanis and Kitsios, 2023). Finally, diverse development teams are essential for reducing algorithmic blind spots, as homogenous groups of engineers may unintentionally embed gender or racial biases into AI systems (Enholm et al., 2022; Jorzik et al., 2024).

Figure 11. AI Responsible Principles. *This framework outlines the core ethical pillars, such as transparency, accountability, and fairness, necessary for responsible AI deployment in organizational context.* ***Source:*** *(Perifanis and Kitsios, 2023)*

Table 2. Summary of AI Tools used in HR

HR Function	AI Tools/Techniques	Benefits/Strategic Outcomes	References
Strategic HRM/ Human Capital Management (RBV Perspective)	AI automation of routine tasks; AI augmented "editor" role; AI reshaping valuable human capital	Strengthens VRIO human capital; Enhances absorptive capacity; Supports innovation & dynamic capabilities; Builds sustained competitive advantage	(Anastasiu et al., 2020; Cuthbertson and Furseth, 2022; Hamadamin and Atan, 2019; Huang et al., 2023; Jaiswal et al., 2022; Kanbach et al., 2024; Kero and Bogale, 2023; Kuncoro and Suriani, 2018; Lanza and Simone, 2025; Morandini et al., 2023; Nonaka and Takeuchi, 2021; Pasban and Nojedeh, 2016)
AI Governance & Organizational Transformation	Generative AI for re-institutionalization; Resource Orchestration; Human-AI error detection roles	Redesign of structures, processes, culture; Integration of AI with human expertise; Empowered teams & improved decision quality	(Chowdhury et al., 2024; Peretz-Andersson et al., 2024)
Organizational Design & Workforce Structuring	AI-enabled resource fluidity; Data-curation roles ("data janitors")	Flexible project-based teams; Better resource allocation; Improved AI reliability	(Chowdhury et al., 2024; Doz, 2020)
Personalized HRM/ Employee Experience	AI-driven personalization; Behavioural analytics; AI-based career pathing & benefits customization	Stronger Person-Organization Fit; Higher affective commitment; Harder-to-imitate human capital	(Căvescu and Popescu, 2025; Huang et al., 2023)

HR Function	AI Tools/Techniques	Benefits/Strategic Outcomes	References
Predictive Analytics for Retention & Engagement	XGBoost, Random Forest; Early Warning Systems; AI-enabled sentiment analysis	Early detection of disengagement; Prevention of burnout; Proactive retention strategies	(Bhosale et al., 2024; Căvescu and Popescu, 2025)
AI-Supported Recruitment	Semantic Analysis; AI resourcing of passive candidates; AI chatbots; Emotion-sensing & computer vision	Faster hiring (up to 90% reduction); Broader talent pool; Improved screening accuracy; Reduced candidate frustration; Potential bias reduction (oversight)	(Enholm et al., 2022; Nawaz et al., 2024; Stone et al., 2024; Vrontis et al., 2022)
Performance Management	Real-time analytics; NLP sentiment analysis; Behavioural monitoring	Continuous, data-driven evaluation; Early burnout detection; Reduced recency bias & favourism	(Bhosale et al., 2024; Stone et al., 2024)
Learning & Development (L&D)	AI-driven LMS ("virtual coaches"); GenAI for training content; Adaptive learning algorithms; Personalized benefits optimization	Tailored learning paths; Lower training development costs; Higher engagement & skill acquisition; Customized benefits packages	(Chowdhury et al., 2024; Huang et al., 2023; Stone et al., 2024)
Upskilling & Organizational Learning	AI-enabled personalized learning; Recommendation algorithms; Intelligent tutoring systems; Gamified simulations	Builds data& algorithmic literacy; Strengthens judgment & "Feeling economy" skills; Supports continuous learning & RO theory	(Dzreke, 2024; Jaiswal et al., 2022; Kanbach et al., 2024; Lanza and Simone, 2025; Morandini et al., 2023; Peretz-Andersson et al., 2024; Stone et al., 2024; Vrontis et al., 2022)

HR Function	AI Tools/Techniques	Benefits/Strategic Outcomes	References
Leadership Development for AI Era	AI-supported leadership analytics; Mobility-based learning pathways	AI Mindset & AI Ambitions; Strategic sensitivity; Psychological safety for experimentation	(Doz, 2020; Enholm et al., 2022; Jorzik et al., 2024; Perifanis and Kitsios, 2023)
Ethical & Responsible AI Capability Building	Human-in-the-loop systems; AI oversight training; Governance frameworks (GDPR, CCPA); Trustworthy AI guidelines	Prevents skill decay; Ensures responsible AI use; Protects privacy & reduces surveillance risks; Strengthens accountability	(Enholm et al., 2022; Khogali and Mekid, 2023; Kumar et al., 2024; Morandini et al., 2023; Perifanis and Kitsios, 2023; Vrontis et al., 2022)
Bias Mitigation & Fairness Management	Bias-detection algorithms; Explainable AI (XAI); Auditing tools for algorithmic fairness	Reduces discriminatory outcomes; Prevents mirroring effect; Enhances transparency & trust	(Enholm et al., 2022; Huang et al., 2023; Janiesch et al., 2021; Khogali and Mekid, 2023; Stone et al., 2024; Vrontis et al., 2022)
Privacy, Surveillance & Data Ethics	Electronic Performance Monitoring (EPM); Wearables & Behavioural tracking; Data-minimization tools	Protects employee privacy; Reduces intrusive monitoring; Ensures informed consent	(Kumar et al., 2024; Nawaz et al., 2024; Vrontis et al., 2022)
Risk Management & AI Accountability	XAI frameworks; Model interpretability tools; Audit trails for automated decisions	Clarifies responsibility; Reduces legal exposure; Supports ethical decision-making	(Janiesch et al., 2021; Jowarder and Jowarder, 2025; Perifanis and Kitsios, 2023; Saranya and Subhashini, 2023)
Diversity, Equity & Inclusion (DEI) in AI Systems	Diverse development teams; Bias-testing datasets	Reduces algorithmic blind spots; Prevents embedding gender/racial bias	(Enholm et al., 2022; Jorzik et al., 2024)

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Chapter 5
Artificial Intelligence as a Direct Source of Competitive Advantage

5.1 AI through the Lens of the VRIO Framework

Examining Artificial Intelligence (AI) through the Resource Based View (RBV) and the VRIO framework, reveals that algorithms themselves are increasingly commoditized, while the strategic advantage lies in how firms combine and manage these resources.

The first VRIO dimension, value, represents the essential threshold: AI must help a firm exploit opportunities or mitigate threats. Research consistently shows that AI satisfies this requirement by improving cost - prediction accuracy and optimizing resource allocation, which enhances operational efficiency and reduces expenses (Mazen et al., 2024). In manufacturing, the integration of AI with IoT generates unique process - optimization capabilities that minimize waste (Hamdouna and Khmelyarchuk, 2025). AI also drives data - enabled business model innovation by supporting digital twins, predictive maintenance and cost - efficient operations (Ghosh, 2025). However, this value is not permanent. Digital resources (data, models and algorithms) degrade over time, meaning they provide a retainable rather than a fully sustainable advantage unless continuously updated (Cuthbertson and Furseth, 2022)

The rarity of AI is shifting away from the technology itself, as foundational models and platforms are now widely accessible (Cuthbertson and Furseth, 2022). What remains rare is “Artificial Intelligence Ambidexterity”, the organizational ability to balance routine AI exploitation with exploratory innovation (Perifanis and Kitsios, 2023). Another critical scarcity lies in “hybrid expertise”, which is professionals who combine technical and business knowledge, exemplified by Pfizer’s “AI Translator" initiative (Dzreke, 2024; Ghosh, 2025). Proprietary data ecosystems also contribute to rarity; for instance, John Deere’s extensive sensor network generates exclusive datasets that competitors cannot easily match.

Inimitability represents the strongest source of long-term advantage and stems not from unbreakable algorithms but from casual ambiguity and social complexity. Competitors may observe an AI system’s outputs but cannot replicate the unique combination of proprietary data, historical learning and human judgment that produced them, an effect clearly visible in Tesla’s closed - loop autonomous driving data ecosystem (Dzreke, 2024). AI becomes truly inimitable only when embedded within specific integration pathways or “human - in - the - loop” configurations. In sectors such as healthcare, the deeply interdependent relationship between algorithmic recommendations and clinical expertise forms a socially complex capability that rivals cannot easily copy. (Dzreke, 2024).

The final VRIO dimension, organization, determines whether a firm can effectively capture the value generated by AI. Resource Orchestration (RO) is especially critical for small and medium sized enterprises, which must structure their data assets, bundle capabilities through learning routines and deploy them to create value (Peretz-Andersson et al., 2024). Strong AI governance also functions as a strategic resource; firms that implement “Responsible AI” frameworks addressing fairness and explainability build trust and resilience that less organised competitors lack (Perifanis and Kitsios, 2023). Ultimately, even advanced algorithms fail to deliver strategic benefits without leadership that cultivates adaptability and an AI - oriented culture (Ghosh, 2025).

In summary, while AI models alone often lead only to competitive parity, sustainable competitive advantage emerges when AI is rare through proprietary data, inimitable through deep workflow integration and fully supported by strong organizational leadership and governance (Dzreke, 2024; Perifanis and Kitsios, 2023).

5.2 AI as a Dynamic Capability

Interpreting AI through the Dynamic Capabilities perspective shifts the strategic emphasis from simply possessing AI technologies to cultivating the organizational capacity to integrate, develop and reconfigure them in response to rapidly changing environments (Hossain et al., 2022; Nonaka and Takeuchi, 2021). Within this view, AI functions as a meta-capability that strengthens the three micro foundations of dynamic capabilities: Sensing opportunities, Seizing resources to capture value and Transforming the organization to ensure continuous renewal (Hossain et al., 2022; Jorzik et al., 2024).

The sensing capability concerns a firm’s ability to scan, explore, and interpret its environment to identify emerging opportunities and threats (Hossain et al., 2022). AI significantly enhances this capability by processing large scale data streams far beyond human cognitive capacity, enabling continuous monitoring of competitor actions and extracting insights from unstructured sources such as social media sentiment (Hossain et al., 2022; Sjödin et al., 2023). Beyond descriptive analysis, AI provides predictive foresight, allowing firms to anticipate shifts in consumer behavior, supply chain disruptions or market volatility (Bhosale et al., 2024; Sjödin et al., 2023). This predictive capability supports “Value Discovery”, enabling firms to identify emerging drivers of change before competitors, as illustrated by Ant Financial’s real time credit risk detection (Dzreke, 2024; Perifanis and Kitsios, 2023).

Once opportunities are identified, AI strengthens the seizing capability by narrowing the gap between insight and action, often through co - creative processes involving customers and ecosystem partners (Sjödin et al., 2023). AI contributes to seizing by automating routine tasks and augmenting complex decision - making, thereby accelerating strategic responsiveness (Hossain et al., 2022; Perifanis and Kitsios, 2023). This rapid mobilization of resources is evident in supply chain operations, where algorithms dynamically optimize routing to prevent disruptions (Peretz-Andersson et al., 2024). Walmart’s ability to automatically reallocate inventory across 10,000 stores during sudden demand surges exemplifies how AI enables firms to exploit market imperfections faster than competitors (Dzreke, 2024).

The transforming capability is the most critical dimension, as it determines whether a firm can continuously reconfigure its asset base to maintain “evolutionary fitness” and overcome organizational inertia (Hossain et al., 2022). AI supports this transformation by enabling market reconfiguration and reconstructing work processes to promote resource fluidity, allowing capital and talent to shift dynamically rather than following rigid annual cycles (Doz, 2020; Hossain et al., 2022). AI also enhances organizational learning through “AI Ambidexterity”, the simultaneous management of exploitation (routine operations) and exploration (innovation) (Perifanis and Kitsios, 2023). This dual capability prevents strategic stagnation by creating continuous feedback loops that refine performance as new data is absorbed (Sjödin et al., 2023).

In summary, competitive advantage in the digital era depends not on the mere possession of AI technologies but on the dynamic capability to orchestrate them, structuring, building and leveraging AI resources to continuously sense market changes, seize emerging opportunities and transform organizational processes (Peretz-Andersson et al., 2024). NVIDIA’s evolution from hardware manufacturer to an orchestrator of the global AI ecosystem illustrates the depth of transformation required to sustain advantage (Dzreke, 2024).

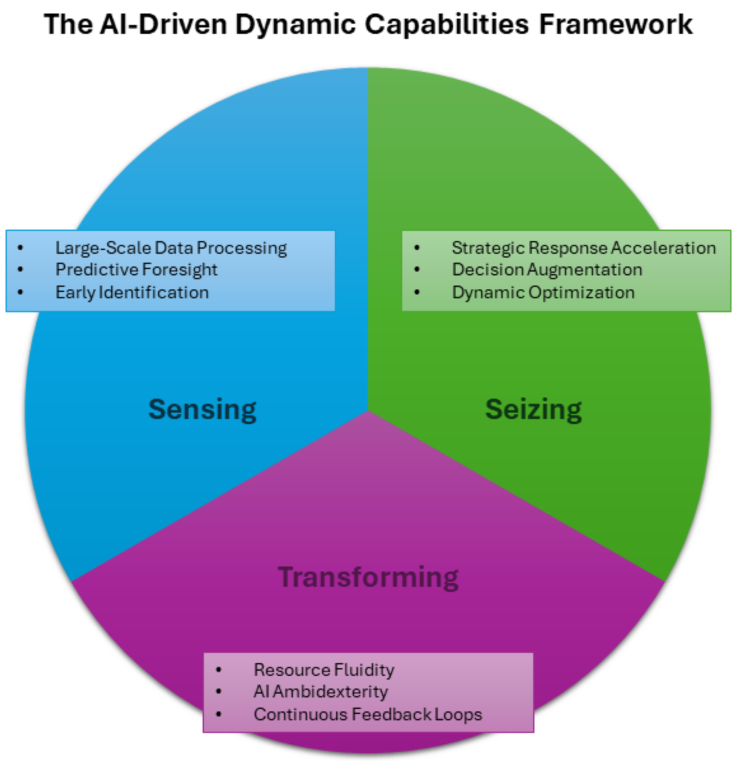

Figure 12. The AI-Driven Dynamic Capabilities Framework. *This figure illustrates how Artificial Intelligence functions as a meta-capability that strengthens the three core foundations of dynamic capabilities. In the Sensing phase, AI enables large-scale data processing and predictive foresight for the early identification of market shifts. During the Seizing phase, it accelerates strategic responsiveness and augments complex decision-making to achieve dynamic optimization. Finally, in the Transforming phase, AI facilitates resource fluidity and "AI ambidexterity" through continuous feedback loops, ensuring continuous organizational renewal.* ***Source:*** *Created by the author, adapted from the literature review and Kao (2025)*

5.3 AI-Enabled Cost Leadership Strategy

AI-Enabled Cost Leadership represents a modern extension of Porter's original cost leadership strategy. Instead of relying mainly on scale advantages or low-cost labor, firms now pursue "dynamic cost optimization", using AI to continuously reduce production expenses, streamline operations, and remove inefficiencies without compromising quality (Jerab and Mabrouk, 2023). Unlike traditional cost-cutting methods based on manual planning or fixed pricing rules, AI provides a flexible and adaptive system that can uncover hidden inefficiencies, such as wasteful packaging or idle resources, that are often overlooked by human decision-makers (Yaiprasert and Hidayanto, 2024).

A key driver of this strategy is Intelligent Process Automation (IPA), which extends automation beyond repetitive tasks to include cognitive activities. In manufacturing, especially in the garment sector, AI-enabled robots have reduced unit production costs by up to 33% by automating complex processes like cutting and screwing (Hossain et al., 2022). Many firms are also adopting "automation business models" using autonomous vehicles and equipment that operate continuously, eliminating operator costs and significantly lowering overall expenses (Sjödin et al., 2023).

AI also reshapes supply chain management by shifting from broad, volume-based strategies to precise, data-driven optimization. In logistics, ensemble machine learning models analyze traffic, weather, and road conditions to generate optimal delivery routes, reducing fuel use and travel time (Patil, 2025; Yaiprasert and Hidayanto, 2024). In inventory management, AI reduces the bullwhip effect by improving demand forecasting accuracy, which lowers storage costs and minimizes waste (Riahi et al., 2021). For procurement, SMEs use AI to detect purchasing patterns and consolidate orders to secure volume discounts that humans may miss (Peretz-Andersson et al., 2024). AI also automates competitive bidding processes to ensure firms consistently obtain the lowest prices (Jackson et al., 2024).

Cost leadership is further strengthened through predictive efficiency and maintenance. PdM uses sensor data to anticipate equipment failures, reducing the financial impact of unexpected breakdowns (Elahi et al., 2023). In mining, for example, AI optimizes vehicle routing and maintenance schedules to prevent collisions and reduce major operational costs (Sjödin et al., 2023), while, AI also manages energy consumption in real-time, such as adjusting mine ventilation based on worker presence, leading to energy savings (Sjödin et al., 2023). Digital Twins further support cost reduction by enabling virtual simulations of production processes, allowing firms to identify bottlenecks without the expense of physical experimentation (Ghosh, 2025).

Achieving AI-enabled cost leadership ultimately depends on effective Resource Orchestration (RO), where firms structure, combine, and deploy AI tools to build capabilities such as predictive modelling (Peretz-Andersson et al., 2024). Interestingly, this strategy also requires empowering employees: by automating routine tasks, AI frees workers to docs on higher-value activities, increasing revenue per employee (Enholm et al., 2022; Peretz-Andersson et al., 2024). However, the success of these systems relies heavily on data quality, making investment in "data janitor" roles essential to prevent inaccurate prediction that could raise rather than reduce costs (Elahi et al., 2023; Nawaz et al., 2024).

5.4 AI-Enabled Differentiation Strategy

AI - Enabled Differentiation Strategy reshapes competitive dynamics by shifting firms away from static product features toward dynamic, data - driven value creation. Through AI, organizations can evolve from mass production to mass personalization and servitization, generating unique offerings that competitors struggle to imitate because they depend on proprietary data ecosystems and sophisticated algorithmic coordination.

A central mechanism of this strategy is Hyper - Personalization, often described as creating a "Segment of One". Traditional differentiation relies on broad segmentation, but AI enables firms to treat each customer as a unique market. By analysing large volumes of unstructured data, such as browsing behaviour, click - through patterns and social media sentiment, AI moves beyond demographic profiling to predict individual preferences (Sarker, 2021). This supports highly tailored "one to one marketing", exemplified by Netflix and Spotify, whose recommender systems curate content so precisely that each user experiences a personalized service (Enholm et al., 2022). AI also enhances contextual differentiation; in the travel sector, for instance, AI generates optimized itineraries based on user constraints, offering a level of customization that static booking platforms cannot match (Borges et al., 2021). Personalization extends internally as well: AI - driven HRM system tailor training, rewards and career development to individual employees, creating a distinctive employer value proposition that is difficult to replicate due to casual ambiguity and path dependence (Huang et al., 2023).

AI further strengthens differentiation by elevating the Customer Experience (CX) through intelligent, responsive interactions. AI powered chatbots and virtual assistants provide continuous availability and with Modern Natural Language Processing (NLP), can resolve complex queries and claims, significantly reducing customer effort (Enholm et al., 2022). A growing differentiator is the ability to scale empathy through sentiment analysis. Tools such as "Tribefinder" analyse communication patterns to detect customer emotions and social "tribes", enabling firms to adjust their messaging in real time to build emotional resonance and reduce churn (Borges et al., 2021; Enholm et al., 2022). AI also shifts CX from reactive to proactive service. In B2B contexts, predictive maintenance identifies equipment issues before they cause downtime, transforming vendor relationships into strategic partnerships centred on customer success (Ghosh, 2025).

Beyond service enhancements, AI enables Novel Product Features and supports "Artificial Creativity", allowing firms to design products that were previously impossible. In engineering, AI mitigates "design fixation" by using Generative Adversarial Networks (GANs) to produce thousands of optimized design alternatives based on performance constraints (Elahi et al., 2023). In the automotive industry, AI transforms vehicles into software - defined platforms capable of autonomy and real - time adaptation (Enholm et al., 2022; Rashid and Kausik, 2024). The rise of GenAI further differentiates digital products by enabling systems to generate code, marketing content or design concepts, expanding the functional scope of software platforms (Jackson et al., 2024; Kanbach et al., 2024).

Sustaining differentiation requires strategic mechanisms that enable AI into the business model. AI enables Data - Driven Business Model Innovation (DDBM), including Digital Servitization, where firms shift from selling products to selling outcomes, supported by AI - guided value capture strategies (Ghosh, 2025). Unlike physical products that depreciate, AI - enabled offerings are "living assets" that improve as they accumulate data, creating strong lock - in effects and increasing switching costs (Kanbach et al., 2024; Sjödin et al., 2023). Leading firms also practice AI Ambidexterity, using AI both for operational efficiency and for exploratory innovation to uncover new market opportunities (Perifanis and Kitsios, 2023). Ultimately, sustainable differentiation does not stem from the algorithm itself, since algorithms can be replicated, but from proprietary data loops and organizational agility that embed AI deeply into the customer value chain (Enholm et al., 2022; Perifanis and Kitsios, 2023).

Table 3. Evolution of Porter's Generic Strategies in the AI Era.

	Traditional	**AI-Enabled**
	Cost Leadership	
Core Cost Drivers	Reliance on economies of scale and low-cost human labor	Dynamic cost optimization with continuous real-time elimination of hidden inefficiencies
Process Execution & Planning	Manual planning, fixed pricing rules, and reactive cost-cutting	Intelligent Process Automation (IPA), which are flexible, adaptive systems that automate complex cognitive and physical tasks

	Traditional	AI-Enabled
Cost Leadership		
Supply Chain & Procurement	**Broad, volume-based strategies with “bullwhip effects”**	**Precise, data-drive optimization with improved demand forecasting**
Asset Maintenance & Energy	Reactive maintenance leading to costly, unexpected equipment failures and static energy usage	Predictive Maintenance (PdM) anticipating failures and real-time energy management
Product Optimization	Expensive, physical trial-and-error experimentation to find bottlenecks	Digital Twins enabling risk-free virtual simulations of production processes
Differentiation		
Product Design & Features	Static product features and standardized physical designs	Dynamic, data-driven features that allow novel, previously impossible product designs
Production & Value Proposition	Mass production focused on delivering uniform physical goods to the market	Mass personalization and servitization, generating unique, living offerings that competitor
Market Segmentation	Broad segmentation relying on generalized demographic profiling	“Segment of One” targeting, treating each customer as a unique market by predicting deep individual preferences
Customer Experience & Service	Reactive service models requiring high customer effort to resolve issues	Proactive service, utilizing advanced natural language processing (NLP) to seamlessly resolve complex queries and significantly reduce customer effort
Internal Capabilities	Standardized, “one-size-fits-all” employee training and development paths	AI-driven HRM systems that uniquely tailor training, rewards, and career development to the individual employee

5.5 AI-Enabled Business Model Innovation

AI - Enabled Business Model Innovation (BMI) marks a shift from traditional product - centric strategies toward data - centric and service - centric architectures. In this transformation, AI functions as a catalyst that reshapes how firms create, deliver and capture value by leveraging data ownership, platform orchestration and network effects.

A core foundation of this shift is the rise of Data - Driven Business Models (DDBM). Although data is often described as the “new oil”, recent research emphasizes that data alone is an operand resource, passive and unable to generate value without operant resources such as algorithms. Moreover, unlike physical assets, the value of data and algorithms deteriorates over time; a search algorithm or customer dataset loses its strategic relevance if not continuously updated. Sustainable advantage therefore depends on a firm’s ability to renew and refresh its data assets and analytical models (Cuthbertson and Furseth, 2022). This has led organizations toward “data industrialization”, where internal operational data, such as logistics logs or transaction histories, is transformed into external, monetizable products like credit scores or consumption indexes (Cao, 2018).

With the emergence of GenAI, firms face a strategic choice between consuming off - the - shelf Large Language Models (LLMs) for rapid deployment or customizing proprietary models. Although customization requires greater investment, it creates a defensible competitive “moat” by preventing data leakage and ensuring the model is uniquely aligned with the firm’s domain (Kanbach et al., 2024).

AI also accelerates the transition from linear value chains to networked ecosystems, positioning the firm as an orchestrator rather than a traditional producer. In this “Orchestrator” model, AI coordinates suppliers, logistics, and customer interactions, reducing transaction costs and operational friction (Mishra and Tripathi, 2021). This enables firms to evolve into intelligent platforms, such as Salesforce or Apple, where Ai supports an ecosystem of third - party developers. The focal firm captures value through subscription or platform fees, while the ecosystem enhances the platform’s overall utility (Ghosh, 2025). Additionally, AI - as - a - Service (AIaaS) allows companies to offer pre - trained models via the cloud, enabling SMEs to access advanced capabilities without major infrastructure investments (Janiesch et al., 2021).

These models are reinforced by the AI Flywheel, a self - reinforcing cycle in which improved products attract more users, generating more data that further enhances the algorithms. Netflix exemplifies this mechanism: hyper - personalization reduces churn, attracts new users and strengthens the platform's intelligence (Mishra and Tripathi, 2021). This creates strategic lock - in, as users lose personalised intelligence if they switch platforms, raising switching costs (Kanbach et al., 2024). Firms like John Deere further strengthen their position through proprietary data collection, such as soil condition data, that competitors cannot replicate simply by purchasing similar software (Dzreke, 2024; Mishra and Tripathi, 2021).

AI also enables Circular and Sustainable Business Models. "Augmentation models" use AI to intensify asset utilization, optimizing fleet routing and building ventilation, to reduce waste and operational costs (Sjödin et al., 2023). "Automation models", based on autonomous vehicles or equipment, dematerialize operations and extend asset lifespan by minimizing human error (Sjödin et al., 2023). AI further supports circularity by predicting component replacement needs and managing refurbishment cycles (Sjödin et al., 2023).

Finally, AI is the central enabler of Digital Servization, shifting firms from selling physical assets (Capex) to selling outcomes (Opex). Through Product - Service Systems (PSS), manufacturers use sensors and predictive maintenance to sell "uptime" or "performance", ensuring profitability through continuous monitoring (Ghosh, 2025). In the GenAI domain, as the marginal cost of content creation approaches zero, business models increasingly shift from creation to curation, with premium offerings emphasizing exclusive or human - curated content (Kanbach et al., 2024).

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Chapter 6
Artificial Intelligence in the Industrial Sector and Competitive Advantage

6.1 AI in Manufacturing and Production

Artificial Intelligence (AI) has reshaped manufacturing by moving beyond basic automation toward “cognitive manufacturing”, where systems can learn, anticipate problems, and adjust their behaviour. This development reflects the broader shift from Industry 4.0, which emphasized data and connectivity, to Industry 5.0, which focuses on closer collaboration between humans and intelligent machines (Gao et al., 2024; Rashid and Kausik, 2024).

Robotics has advanced in the same direction. Instead of relying on rigid, pre-programmed instructions, modern robots use AI to perceive their surroundings and adapt to variation. A major innovation is Human-Robot Collaboration (HRC), where robots can interpret human intentions and assist proactively. Deep learning models such as Convolutional Neural Networks (CNNs) analyse signals like gaze direction or muscle activity to recognize actions, for example, tightening screws, so the robot can hand over tools at the right moment and reduce physical strain on workers (Gao et al., 2024). AI also enables robots to manipulate flexible materials such as wires or fabrics using Reinforcement Learning (RL), which teaches robots through trial and error (Gao et al., 2024).

These capabilities extend into Robotic Process Automation (RPA) and sector-specific applications. In the apparel industry, AI-driven robots have lowered production costs by 33% by automating complex tasks like cutting and sewing, which were traditionally difficult due to material flexibility (Hossain et al., 2022). In warehousing, AI-enabled robots equipped with sensors can identify, pick, and transport items continuously, reducing labour costs and increasing operational efficiency (Patil, 2025). On the factory floor, Autonomous Mobile Robots (AMRs) use Multi-Agent Reinforcement Learning (MARL) to navigate dynamic environments, cooperate with other robots, and avoid obstacles in real time (Gao et al., 2024). Generative grasping techniques further allow robots to handle unfamiliar objects by predicting optimal grasp points through self-supervised learning (Gao et al., 2024).

AI also enhances the physics of manufacturing processes. In Addictive Manufacturing (3D printing), machine learning models such as Support Vector Machines (SVM) and Neural Networks analyse how laser power, scan speed, and material properties interact, helping predict melt pool behaviour and prevent defects (Elahi et al., 2023). In Subtractive Manufacturing, AI performs “smart tuning” to forecast surface roughness, tool wear, and energy consumption, with Random Forest models often outperforming traditional physics-based equations (Elahi et al., 2023; Gao et al., 2024). Computer vision systems can also detect metal chip buildup in computer numerical control (CNC) machines and generate automated cleaning paths (Gao et al., 2024). In the design phase, Generative Adversarial Networks (GANs) and Topology Optimization allow engineers to input constraints and generate thousands of optimized geometries that are often lighter and stronger than human-designed alternatives (Elahi et al., 2023).

Beyond individual machines, AI supports system-level optimization across entire production facilities. AI-enabled energy management systems can significantly reduce consumption, ventilation systems in mining operations, for instance, can cut energy use by 54% by directing airflow only to occupied areas (Sjödin et al., 2023). In battery production, machine learning-based sensitivity analysis helps identify key variables that can deliver energy savings of up to 9% (Gao et al., 2024).

These technologies converge within the broader “Smart Factory” ecosystem. A foundational element in the Digital Twin (DT), a virtual model of physical assets enhanced with physics-based simulations and analytics to predict machine health and test production scenarios before implementation (Ghosh, 2025). This concept evolves into the “Digital Triplet", which incorporates human expertise alongside physical and virtual models to manage retrofitted equipment (Elahi et al., 2023). Predictive Maintenance (PdM) uses Long Short-Term Memory (LSTM) networks and Autoencoders to estimate the Remaining Useful Life (RUL) of components by analysing vibration and thermal data (Elahi et al., 2023). Quality assurance is automated through deep learning models such as YOLO, which detect and classify surface defects to reduce waste (Elahi et al., 2023; Jackson et al., 2024). Finally, AI supports “smart retrofitting” by analysing sensor data from legacy equipment and improves energy efficiency by scheduling energy-intensive tasks during off-peak hours (Elahi et al., 2023; Gao et al., 2024).

In summary, AI is fundamentally transforming manufacturing by integrating intelligent robotics, process optimization, and data-driven management into a cohesive and adaptive ecosystem. This shift represents an evolution from isolated automation tools to interconnected systems that possess the capacity to learn, predict, and collaborate with human operators. As the concept of Industry 5.0 advances, future competitive advantage will rely not merely on the adoption of these technologies, but on their strategic integration to augment human expertise, promote sustainability, and ensure operational precision and resilience.

6.2 Predictive Maintenance and Asset Management

Predictive Maintenance (PdM) functions as the “immune system” of the smart factory, marking a shift away from reactive repairs and routine scheduled servicing toward AI-driven systems that anticipate failures before they occur. This approach depends on the continuous monitoring of equipment through IoT sensors that capture data on temperature, vibration, pressure, and electrical activity to assess machine health (Ekene Cynthia Onukwulu et al., 2021). While traditional machine learning can support this process, DL has become increasingly important for interpreting complex and unstructured data. For example, Convolutional Neural Networks (CNNs), commonly used in visual inspection, can also analyse acoustic and vibration signals to detect subtly mechanical defects (Khedr and S, 2024). Recurrent Neural Networks (RNNs) and LSTM models are particularly valuable for time-series analysis, enabling systems to capture long-term patterns and estimate the Remaining Useful Life (RUL) of equipment (Khedr and S, 2024). Instead of relying on fixed rules, these models learn baseline operating behaviour and identify anomalies when equipment deviates from expected patterns (Peretz-Andersson et al., 2024).

The economic benefits of AI-enabled maintenance are significant. By replacing scheduled servicing with condition-based interventions, firms avoid unnecessary maintenance and reduce the risk of costly, unplanned breakdowns (Ekene Cynthia Onukwulu et al., 2021). PdM also supports sustainability goals within Green Supply Chain Management (GSCM). Timely maintenance prevents severe equipment damage, extends asset lifespan, and reduces the need for replacement parts (Patil, 2025). AI can further optimize energy consumption by analysing operational conditions; for instance, systems like Enerbrain use real-time forecasting to adjust HVAC usage, lowering energy demand while maintaining performance (Ekene Cynthia Onukwulu et al., 2021). Maintaining machines at optimal performance also reduces scrap, defects, and material waste, supporting circular economy practices (Sodiq Fowosere et al., 2025).

Practical applications across industries demonstrate the versatility of PdM. In maritime logistics, Maersk employs AI and IoT to predict failures in ships and port equipment, reducing downtime and improving fuel efficiency (Bhuvaneswari, 2025). In oil and gas, companies such as BP and Shell use PdM on offshore rigs to analyse sensor data from pumps and compressors, improving safety and operational reliability (Ekene Cynthia Onukwulu et al., 2021). Smaller manufacturers in Sweden use IoT sensors to track cooling water flow and temperature variations, identifying early signs of equipment degradation (Peretz-Andersson et al., 2024). In the utilities sector, firms like PG&E apply machine learning to forecast electricity demand and optimize grid performance using historical and weather data (Ekene Cynthia Onukwulu et al., 2021).

Despite its advantages, AI-based asset management faces several challenges. High-quality, well-integrated data is essential, yet many organizations struggle to combine information from legacy systems, outdated sensors, and fragmented ERP platforms (Khedr and S, 2024). Training advanced deep learning or transformer models for real-time monitoring also requires substantial computational resources and energy, which can be difficult for smaller firms to support (Aylak, 2025). Additionally, the “Black Box” nature of deep learning remains a barrier; when models cannot explain their predictions, technicians may be reluctant to rely on them for critical maintenance decisions (Khedr and S, 2024).

In conclusion, Predictive Maintenance has become a cornerstone of modern asset management, enabling factories to shift from reactive and schedule-based repairs to intelligent, condition-driven interventions. By combining IoT data with advanced machine learning and deep learning models, organizations can prevent failures, reduce waste, and extend the lifespan of critical equipment. Although challenges remain, such as data integration, computational demands, and the opacity of complex models, the strategic value of PdM is clear. Firms that successfully implement these systems gain not only operational efficiency but also greater sustainability, resilience, and competitiveness in increasingly data-intensive industrial environments.

6.3 AI in Supply Chain Optimisation

Supply Chain Optimisation (SCO) is undergoing a major transformation, shifting from reactive coordination to autonomous, self-adjusting systems. Recent research shows that AI is no longer limited to forecasting outcomes; it now actively manages and reallocates resources through Agent AI and Generative models to optimize cost, efficiency, and environmental performance.

Forecasting has progressed far beyond traditional statistical methods. Instead of relying solely on historical sales data, modern systems use DL models capable of processing real-time, unstructured information, such as weather conditions, market signals and economic indicators, to anticipate fluctuations. Architecture like LSTM networks and RNNs have become standard tools for time-series forecasting because they capture long-term patterns and dependencies with high accuracy (Jackson et al., 2024; Khedr and S, 2024). Generative AI extends this capability by simulating a wide range of marker scenarios. By generating synthetic data, firms can stress-test their supply chains against rare, high-impact disruptions, called “black swan” events, improving preparedness and resilience (Jackson et al., 2024; Patil, 2025). A major step forward is the emergence of Agentic AI, which autonomously executes decisions rather than merely advising managers. For example, the SustAI-SCM framework uses transformer-based models that continuously learn from operational feedback, adjusting procurement and inventory in real-time to reduce emissions and cut costs (Aylak, 2025).

In logistics, AI enhances both last-mile delivery and global freight operations by solving complex routing and scheduling problems while supporting Green Supply Chain Management (GSCM). Unlike static routing systems, AI models incorporate real-time data, such as traffic, weather, accidents, and road closures, to instantly update delivery paths reducing delays and fuel consumption (Bhuvaneswari, 2025; Patil, 2025). The literature highlights the use of bio-inspired algorithms such as Genetic Algorithms (GA) for multi-objective optimization and Particle Swarm Optimization (PSO) for designing efficient logistics networks (Riahi et al., 2021). AI also plays a central role in decarbonization efforts. By optimizing truckloads and minimizing “empty miles”, machine learning models significantly reduce greenhouse gas emissions (Mrad et al., 2025; Sodiq Fowosere et al., 2025). AI-enabled multimodal transport strategies have been shown to lower both operational costs and carbon output (Mrad et al., 2025).

Warehousing has similarly evolved into a highly automated, intelligent environment. Autonomous Mobile Robots (AMRs), such as Amazon’s Kiva systems, use sensors and computer vision to navigate warehouses, retrieve items, and support packing operations, reducing labour costs and human error (Bhuvaneswari, 2025). Some facilities employ swarm robotics to collaboratively move heavy goods (Mrad et al., 2025). Inside the warehouse, CNNs analyse video streams to detect damaged packaging or product defects before shipment, reducing returns and waste (Jackson et al., 2024; Patil, 2025). Advanced warehouses also rely on Digital Twins, which are virtual models of the physical supply chain, to test layout changes or process improvements before implementing them in real operations (Mrad et al., 2025). Finally, AI continuously analyses order patterns to organize warehouse layouts, placing high-demand items closer to packing stations to reduce travel time and improve fulfilment speed (Patil, 2025; Sodiq Fowosere et al., 2025).

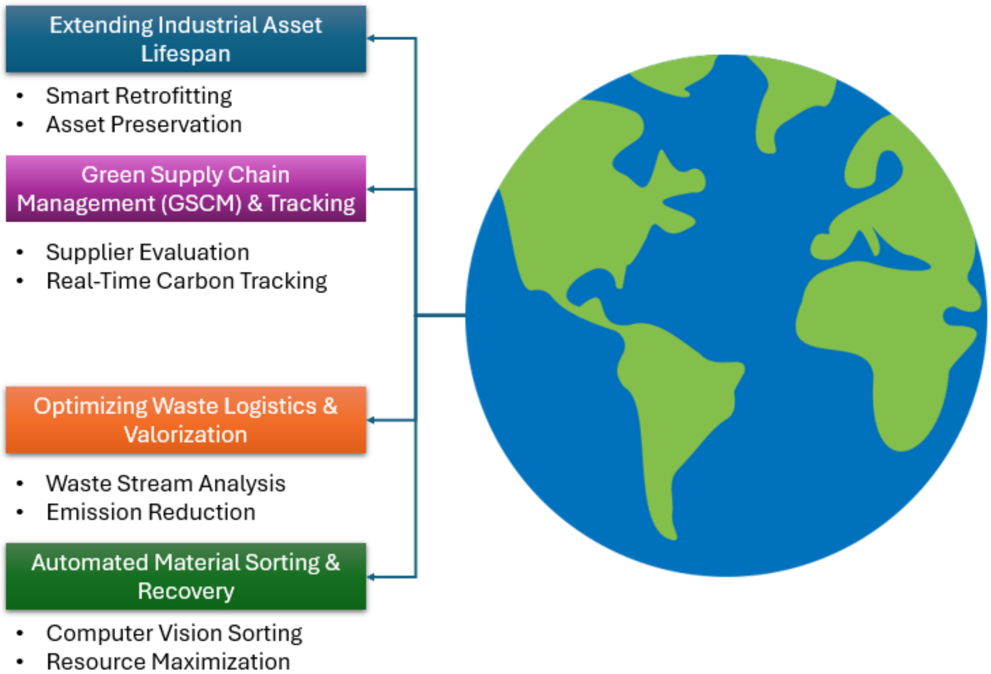

Figure 13. AI's Role in Advancing the Circular Economy. *This figure outlines how AI drives the circular economy: extending asset lifespans, optimizing green supply chains, improving waste logistics, and automating material recovery.* ***Source:*** *Created by the author based on literature review. Globe icon by IconsNova via Freepik.*

6.4 AI for Energy Efficiency and Sustainability

Artificial intelligence is reshaping Energy Efficiency and Sustainability by shifting the field from passive monitoring to active, autonomous optimization of energy systems. AI now plays a central role in integrating renewable energy into the grid, improving industrial energy performance through smart retrofitting, and supporting circular economy practices.

One of the biggest challenges in renewable energy is its variability, which can destabilize power grids. AI addresses this by forecasting fluctuations and balancing loads in real time. ML models analyse historical consumption data, weather forecasts, and economic indicators to predict demand accurately, helping utilities avoid unnecessary increase in fossil-fuel production during peak periods (Ekene Cynthia Onukwulu et al., 2021). AI is also essential for managing the intermittency of solar and wind power. LSTM networks, for example, forecast solar output using historical patterns, enabling smart grids to remain stable even when weather conditions change (Ekene Cynthia Onukwulu et al., 2021; Jackson et al., 2024). Emerging research suggests that AI will further strengthen grid resilience by autonomously detecting faults and outages, making energy systems more adaptable to decentralized renewable sources (Ekene Cynthia Onukwulu et al., 2021).

A key but often overlooked sustainability strategy is extending the lifespan of existing industrial assets. Through “smart retrofitting”, older machines are equipped with sensors and ANNs, enabling them to monitor their own energy use and thermal behaviour (Elahi et al., 2023). This reduces the environmental impact associated with manufacturing new equipment and significantly prolongs asset life (Elahi et al., 2023). DL is also used to optimize embedded system design by predicting heat transfer parameters, ensuring efficient cooling and reducing industrial energy consumption (Elahi et al., 2023). In logistics, AI-driven robotics can cut warehouse energy use by up to 20% by optimizing robot movement and handling speed (Mrad et al., 2025).

AI is also accelerating the shift from a linear “take-make-dispose” model to a Circular Economy. AI and IoT systems optimize waste logistics and “valorisation” by analysing waste streams to identify materials suitable for recycling or pyrolysis, directly lowering greenhouse gas emissions (Mrad et al., 2025). Computer Vision technologies automate the sorting of recyclable materials by distinguishing between different material types, ensuring that valuable resources are recovered instead of discarded (Jackson et al., 2024). AI tools also support GSCM by evaluating suppliers’ environmental performance and using Big Data Analytics (BDA) to track carbon footprints across the supply chain (Sodiq Fowosere et al., 2025).

The latest development in this field is Agentic AI, which are autonomous systems that not only predict emissions but actively work to reduce them. Unlike static rule-based tools, Agentic AI models such as SustAI-SCM framework continuously learn from global traffic and environmental data to adjust logistics routes in real time (Aylak, 2025). Experimental results show that this autonomous eco-routing can reduce fuel consumption by 22.8% and cut carbon emissions by 30.3% (Aylak, 2025). These systems also provide real-time visibility into environmental impacts, enabling organizations to track sustainability performance continuously rather than relying on periodic audits (Aylak, 2025; Sodiq Fowosere et al., 2025).

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Chapter 7
Artificial Intelligence in the Services Sector and Competitive Advantage

7.1 AI in finance and Banking

Artificial Intelligence has shifted from a back-office support tool to a strategic capability in finance and banking, transforming how institutions manage risk, conduct trading, and deliver customer services. One of the most important applications of AI in this sector is fraud detection and regulatory compliance. AI and Machine Learning (ML) systems can process enormous volumes of data to identify unusual patterns and detect scams in real time (Mahalakshmi et al., 2022). By examining behavioural indicators such as a customer's location or spending profile, these systems can automatically block suspicious transactions and significantly reduce false positives (Mahalakshmi et al., 2022). The accuracy gains are substantial; for example, Ernst & Young's Fraud Investigation and Dispute service achieved 97% accuracy in detecting suspicious invoices using ML (Zhang et al., 2020). Financial institutions increasingly rely on hybrid AI models that combine neural networks with fuzzy logic to detect anomalies in transaction data (Corral de la Mata et al., 2024). In auditing, tools such as "AI Extractor" automate control checks and payment preparation more effectively than traditional optical character recognition (Zhang et al., 2020). AI also strengthens Anti-Money Laundering (AML) processes by identifying financial crimes and reducing the cost and workload associated with investigations (Mahalakshmi et al., 2022).

In investment activities, algorithmic trading (algo trading) uses automated systems to execute trades based on predefined rules related to timing, price, and quantity (Mahalakshmi et al., 2022). A major advantage is the removal of emotional bias; algorithms respond to market changes objectively and avoid the behavioural pitfalls that affect human traders (Mahalakshmi et al., 2022). ML has been shown to improve trade settlement efficiency by 64% and can even predict potential business failures (Mahalakshmi et al., 2022). The technologies also support high-frequency trading and automate processes that were previously manual (Mahalakshmi et al., 2022).

AI has also broadened access to wealth management through Robo-Advisors, digital platforms that use statistical models and algorithms to manage investment portfolios according to a client's risk tolerance and financial objectives (Corral de la Mata et al., 2024; Mahalakshmi et al., 2022). These tools are typically less expensive than human advisors and offer advanced features such as tax optimization (Corral de la Mata et al., 2024; Mahalakshmi et al., 2022). In retail banking, AI-driven personalization has become a strong predictor of customer loyalty, as tailored recommendations increase satisfaction and emotional connection (Yousaf et al., 2025). However, despite improving trust, AI still struggles to replicate human empathy, creating a “service gap” in emotionally sensitive interactions (Yousaf et al., 2025).

AI is also reshaping credit risk assessment and operational efficiency. By analysing unstructured data, such as social media activity, AI can generate a more comprehensive picture of a borrower’s creditworthiness, enabling automated loan decisions within seconds (Corral de la Mata et al., 2024). Banks are increasingly using Robotic Process Automation (RPA) to manage repetitive, high-volume tasks like account reconciliation, reducing human error and freeing staff for higher-value work (Corral de la Mata et al., 2024). A major limitation, however, is the “black box” problem: complex AI often lacks transparency, making it difficult to understand or justify their decisions, which raises concerns for trust and regulatory compliance (Yang et al., 2024b, 2024a).

Overall, AI has become a driver of competitive intelligence, enabling financial institutions to enhance security, identify new revenue opportunities, and improve operational performance (Mahalakshmi et al., 2022). Yet successful adoption requires a hybrid approach in which human expertise complements AI, especially in areas involving ethical judgment and customer relationships (Yousaf et al., 2025).

Table 4. AI Applications Across Finance and Banking Sectors

Finance Sector	AI Application	Reference
Fraud Detection and Compliance	Process enormous volumes of data to identify unusual patterns and detect scams in real life	Mahalakshmi et al., 2022
	Automatically block suspicious transaction and reduce false positives	
Fraud Detection and Compliance	Automate control checks and payment preparation	Zhang et al., 2020
	Strengthen Anti-Money Laundering (AML) processes	Mahalakshmi et al., 2022

Finance Sector	AI Application	Reference
Investment and Trading	Algorithmic trading executes trades based on predefined rules	Mahalakshmi et al., 2022
	Algorithms respond objectively to market changes	
	Improve trade settlement efficiency and predict business failures	
	Support high-frequency trading and automate previously manual processes	
	Manage investment portfolios based on risk tolerance and financial goals	Corral de la Mata et al., 2024; Mahalakshmi et al., 2022
Retail Banking	Personalized recommendations for customers	Yousaf et al., 2025
Credit Risk Assessment	Analyse unstructured data to assess creditworthiness	Corral de la Mata et al., 2024
Operational Efficiency	Automate repetitive, high-volume tasks such as account reconciliation	

7.2 AI in Healthcare and Patient Management

Just as AI has transformed financial services by improving fraud detection and enabling personalized financial guidance, it is now reshaping healthcare, arguably with even greater societal impact. Instead of focusing on financial risk, AI technologies such as Machine Learning (ML), Deep Learning (DL) and Natural Language Processing (NLP) are being applied to safeguard patient health, enhance diagnostic accuracy and optimize clinical workflows.

AI has progressed from basic data analysis to advanced systems capable of interpreting medical images with accuracy comparable to (and in some cases exceeding) human specialists. In radiology and medical imaging, Convolutional Neural Networks (CNNs) are widely used to analyse X - rays, CT scans and MRIs (Bekbolatova et al., 2024; Poalelungi et al., 2023). These models can detect subtle abnormalities, such as small fractures, early tumours or early cardiovascular indicators, that may be overlooked by clinicians (Bekbolatova et al., 2024). AI systems have shown particular success in identifying lung nodules earlier than radiologists, reducing diagnostic delays (Dangi et al., 2025). In breast cancer screening, AI has reduced both false positives and false negatives, outperforming radiologists in detecting early stage disease (Alowais et al., 2023).

These diagnostic advances extend across multiple medical specialities. In cardiology, AI analyses ECGs and echocardiograms to detect arrhythmias and predict cardiovascular events (Al Kuwaiti et al., 2023; Poalelungi et al., 2023). Deep Learning models have also demonstrated superior accuracy in predicting heart failure and assessing cardiac risk compared to traditional tools like the Flamingham score (Bekbolatova et al., 2024; Dangi et al., 2025). In pathology and dermatology, AI assists in classifying tissue samples and skin lesions, achieving performance comparable to expert clinicians (Bekbolatova et al., 2024; Poalelungi et al., 2023). During the COVID - 19 pandemic, AI played crucial role in screening patients using chest CT scans to detect SARS - CoV - 2 infection, especially when PCR testing capacity was limited (Al Kuwaiti et al., 2023; Bekbolatova et al., 2024).

Beyond diagnostics, AI addresses major inefficiencies in pharmaceutical development by accelerating drug discovery. Bioinformatics and cheminformatics models help identify promising compounds and validate drug targets more quickly (Al Kuwaiti et al., 2023; Poalelungi et al., 2023). Through molecular docking simulations, AI predicts drug - protein interactions, reducing laboratory trial - and - error (Bekbolatova et al., 2024). AI also supports drug repurposing, identifying new uses for existing medications, and predicts toxicity early in development, preventing costly late-stage failures (Al Kuwaiti et al., 2023; Alowais et al., 2023). During the pandemic, AI helped analyze viral protein structures to identify immunogenic targets, accelerating vaccine development (Al Kuwaiti et al., 2023; Bekbolatova et al., 2024).

AI also enables precision medicine, shifting healthcare away from generalized treatments toward interventions tailored to an individual's genetic profile, lifestyle and clinical history (Alowais et al., 2023). ML models analyse genomic datasets to identify disease related variants, enabling clinicians to classify patients into molecular subtypes and select targeted therapies (Alowais et al., 2023). Platforms such as CURATE.AI optimize drug dosages dynamically; in chemotherapy, for example, AI maps the relationship between drug intensity and patient response to recommend personalized dosing that maximizes effectiveness while minimizing toxicity (Alowais et al., 2023; Poalelungi et al., 2023). AI models using Electronic Health Records (EHRs) have also predicted treatment responses, such as antidepressant effectiveness, with accuracy rates above 80% (Alowais et al., 2023).

AI is equally transformative in-patient management and administrative operations. The integration of AI with IoT devices and wearables enables Remote Patient Monitoring (RPM), allowing continuous tracking of vital signs outside clinical settings (Al Kuwaiti et al., 2023; Ali et al., 2023). AI analyses this real - time data to detect early deterioration and alert clinicians before conditions escalate (Al Kuwaiti et al., 2023; Dangi et al., 2025). AI - powered virtual assistants support triage, reduce unnecessary hospital visits and even assist in mental health management; for example, the Woebot app has been linked to reductions in depression and anxiety (Alowais et al., 2023). Operationally, NLP automates clinical documentation and populates EHRs, reducing administrative burden and allowing clinicians to spend more time with patients (Al Kuwaiti et al., 2023; Bekbolatova et al., 2024).

Despite these advances, AI in healthcare faces challenges similar to those in finance, particularly the "black box" problem, where reasoning behind algorithmic decisions is not transparent (Al Kuwaiti et al., 2023). Additional barriers include data privacy concerns, risks of algorithmic bias, such as racial or gender disparities in diagnostic models, and the need for strong regulatory frameworks to ensure safe and ethical deployment (Al Kuwaiti et al., 2023; Bekbolatova et al., 2024).

Table 5. AI Applications in Healthcare Sector

Healthcare Sector	AI Application	Reference
Diagnostic Advances - Medical Imaging	Analyses X-rays, CT scans and MRIs, detecting subtle abnormalities earlier than clinicians.	Bekbolatova et al., 2024; Poalelungi et al., 2023
	Identifies lung nodules earlier than radiologists, reducing diagnostic delays and improving early detection.	Dangi et al., 2025

Healthcare Sector	AI Application	Reference
Diagnostic Advances - Medical Imaging	Reduces false positives and false negatives in breast cancer screening, outperforming radiologists in early-stage detection.	Alowais et al., 2023
Diagnostic Advances - Cardiology	Analyses ECGs and echocardiograms, detecting arrhythmias and predicting cardiovascular events	Al Kuwaiti et al., 2023; Poalelungi et al., 2023
Diagnostic Advances - Pathology & Dermatology	Classifies tissue samples and skin lesions achieving expert-level diagnostic accuracy	Bekbolatova et al., 2024, Poalelungi et al., 2023
Pharmaceutical Development	Bioinformatics & cheminformatics models accelerate drug discovery, identifying promising compounds and validating drug targets faster	Al Kuwaiti et al., 2023; Poalelungi et al., 2023
	Predicts drug-protein interactions, reducing laboratory trial-and-error	Bekbolatova et al., 2024
	Supports drug repurposing and early toxicity prediction, preventing costly late-stage failures	Al Kuwaiti et al., 2023; Alowais et al., 2023
	Analyses viral protein structures, accelerating vaccine development	Al Kuwaiti et al., 2023; Bekbolatova et al., 2024
Precision Medicine	Shifts care toward individualized treatments, tailoring interventions to genetics, lifestyle, and clinical history	Alowais et al., 2023
	Analyses genomic datasets, identifying disease-related variants and supporting molecular subtyping	Alowais et al., 2023

Healthcare Sector	AI Application	Reference
Precision Medicine	Optimizes drug dosages dynamically, maximizing treatment effectiveness and minimizing toxicity	Alowais et al., 2023; Poalelungi et al., 2023
	Uses electronic health records (EHRs) to predict treatment responses, achieving high accuracy and supporting personalized therapy	Alowais et al., 2023
Patient Management & Remote Monitoring	Along with IoT wearables, enable Remote Patient Monitoring (RPM), allowing continuous vital-sign tracking outside clinical settings	Al Kuwaiti et al., 2023; Ali et al., 2023
	Chatbots support triage and mental health, reducing unnecessary visits and improving mental-health outcomes	Alowais et al., 2023
Administrative & Clinical Operations	Automates clinical documentation and EHR population, reducing administrative burden and increasing clinician time with patients	Al Kuwaiti et al., 2023; Bekbolatova et al., 2024

7.3 AI in Retail and Customer Experience

The literature shows that AI is reshaping the retail sector in a way that mirrors its impact on finance and healthcare, shifting from a narrow focus on operational efficiency toward deeply personalized and emotionally intelligent customer engagement. By leveraging large - scale data through AI and ML, retailers are increasingly able to merge the convenience of e-commerce with the experimental value of physical stores.

AI - powered chatbots and virtual assistants now function as the primary interface between retailers and customers. These systems have evolved far beyond rule - based scripts, offering responsive and context - aware interactions. They provide continuous, 24/7 support and significantly reduce waiting times; one study reported a drop in average response time from 10 minutes to just 2, after deploying AI - driven assistants (Satish Krishnamurthy et al., 2024). By managing up to 80% of routine inquiries, these tools free human agents to focus on more complex cases, reducing operational costs by as much as 60% (Ahamed, 2025). Modern conversational

AI systems also incorporate NLP to detect customer emotions with accuracy rates up to 82%, enabling them to adjust tone or escalate interactions when frustration is detected (Ahamed, 2025; Kumar and Koshy, 2025). Despite the advances, customer acceptance is not universal; some studies indicate that users still prefer human agents, especially when bots conceal their identity or when queries are complex (Guha et al., 2021). Nevertheless, as conversational systems become more human - like and capable of maintaining long - form context, engagement rates have increased by approximately 32% (Ahamed, 2025).

Recommendation engines represent another major pillar of AI - enabled differentiation in retail. These systems analyse browsing behaviour, purchase history and demographic data to deliver highly personalized product suggestions. Retailers report substantial financial gains from these tools, including sales increases of up to 50% and a 40% rise in average order value (Satish Krishnamurthy et al., 2024). Personalization also strengthens customer loyalty, with studies showing a 40% improvement in retention rates due to advanced recommendation systems (Ahamed, 2025). These engines typically rely on Collaborative Filtering, identifying patterns among similar users, and Content - Based Filtering, which recommends products with attributes aligned to a customer's past preferences (Satish Krishnamurthy et al., 2024). Deep learning and neural networks have further enhanced these systems, enabling real - time analysis of millions of transactions and identifying subtle product relationships with up to 95% accuracy (Ahamed, 2025).

AI is also transforming pricing strategies through dynamic pricing, replacing static, historically based models with real - time adjustments driven by demand, competition and inventory levels. AI systems continuously analyse market conditions and competitor prices to determine optimal pricing, lowering prices for overstocked items or increasing them during periods high demand (Satish Krishnamurthy et al., 2024). In physical stores, this capability is supported by Electronic Shelf Labels (ESLs), which allow instant price updates and notify staff about items needed for online order fulfilment (Grewal et al., 2023). AI also enables personalized pricing, offering targeted discounts based on customer loyalty, behaviour and price sensitivity (Satish Krishnamurthy et al., 2024).

These technologies collectively support a broader Omnichannel strategy, creating a seamless "Phygital" experience that integrates online and offline retail. AI facilitates hybrid behaviours such as SOPIS (Search Online, Purchase In - Store) through tools like NearSt and Pointy, which provide real - time visibility into local store inventory (Grewal et al., 2023). Within physical stores, AI - enabled smart mirrors, such as “Magic Mirrors” in fashion retail, allow customers to virtually try on clothing, enhancing convenience and reducing fitting room friction (Grewal et al., 2023; Guha et al., 2021).

However, the literature highlights an ongoing tension between personalisation and privacy. While customers appreciate tailored experiences, trust depends on transparent communication about how their data is collected and used (Kumar and Koshy, 2025; Spring et al., 2022). Despite these concerns, the evidence suggests that AI has become a strategic imperative for retailers seeking to maintain profitability and meet rapidly evolving consumer expectations (Satish Krishnamurthy et al., 2024; Yousaf et al., 2025).

Table 6. Applications in Retail and Customer Experience

Retail Sector	AI Application	Reference
Chatbots & Virtual Assistants	Provide responsive, context-aware interaction with 24/7 availability, reducing waiting times and dropping response time from 10 to 2 minutes	Satish Krishnamurthy et al., 2024
	Handle up to 80% of routine inquiries freeing human agents for complex cases, and reducing operational costs up to 60%	Ahamed, 2025
	Use Neuro-Linguistic Programming (NLP) to detect customer emotions with up to 82% accuracy adjusting tone and escalating when frustration is detecting, thus improving service quality	Ahamed, 2025; Kumar and Kosh, 2025
Chatbots & Virtual Assistants	Maintain long-form context and human-like interaction, increasing engagement rates by ~32%	Ahamed, 2025
Recommendation Engines	Analyse browsing behaviour purchase history and demographics, delivering personalized product suggestions and increasing sales up to 50%	Satish Krishnamurthy et al., 2024
	Personalization strengthens customer loyalty, thus improving retention rates by 40%	Ahamed, 2025

Retail Sector	AI Application	Reference
Recommendation Engines	Use Collaborative Filtering and Content-Based Filtering, matching products to user preferences and improving relevance	Satish Krishnamurthy et al., 2024
	Deep Learning enables real-time analysis of millions of transactions, identifying subtle product relationships up to 95% accuracy	Ahamed, 2025
Pricing Strategies	Dynamic pricing adjusts prices in real time based on demand, competition and inventory, leading to optimized pricing, reduced overstock losses and increased revenue during high demand	Satish Krishnamurthy et al., 2024
	Personalized pricing based on loyalty, behaviour and price sensitivity, leading to targeted discounts and improved conversion rates	
Omnichannel Retail & In-Store Experience	Tools like NearSt and Pointy provide real-time visibility into local inventory, enabling SOPIS (Search Online Purchase In-Store) and supporting hybrid shopping behaviour	Grewal et al.,2023
	AI-enabled smart mirrors (“Magic Mirrors”) allow virtual try-ons, reducing fitting-room friction, enhancing convenience and improving customer satisfaction	Grewal et al.,2023; Guha et al., 2021

7.4 AI in Professional Services

Artificial Intelligence is reshaping the knowledge foundations of Professional Services Firms (PSFs), shifting their competitive advantage from individual human expertise toward data - driven systems and algorithmic intelligence (Bezuidenhout et al., 2023). This transformation is most visible in the automation of routine, repetitive tasks, which enables firms to redirect human effort toward higher value advisory and analytical work.

The accounting profession is currently leading this transition. Beyond basic computational tasks, firms now deploy Robotic Process Automation (RPA) to manage rule - based activities such as data entry, invoice processing and tax preparation (Zhang et al., 2020). RPA tools can perform tasks like submitting forms to tax authorities or executing three - way matching in procurement, freeing accountants to focus on interpretation and judgment (Zhang et al., 2020). A major shift enabled by AI is the move from sampling to full - population analysis: whereas manual audits could only examine a fraction of transactions, AI systems can analyse 100% of journal entries to detect anomalies, patterns or potential fraud in real time (Spring et al., 2022). Supporting technologies include NLP, which interprets unstructured documents such as contracts and board minutes to identify compliance risks, and ML tools like PwC’s GL.ai, which learns from global datasets to flag unusual ledger entries (Zhang et al., 2020). Even physical audit procedures are being augmented, with firms such as EY using drones to conduct inventory observations and real - time stock verification (Zhang et al., 2020).

In the legal sector, AI is transforming how lawyers process large volumes of text and assess case outcomes, challenging the traditional billable hour model. NLP accelerates document review and due diligence; one case study describes a law firm analysing thousands of leases to identify clauses related to regulatory changes, an effort completed in two weeks that would have been infeasible manually (Spring et al., 2022). Predictive analytics is also used to forecast litigation outcomes by examining historical case law and judge behaviour (Bezuidenhout et al., 2023). Some firms now offer AI - based self - service tools that allow clients to review simple contracts independently, generating guidance based on encoded legal expertise (Spring et al., 2022). Blockchain further supports automation through smart contracts that execute transactions automatically when predefined conditions are met, reducing the need for legal intermediaries (Zhang et al., 2020).

Consulting firms, often described as “Neo - PSFs”, are also undergoing significant transformation as AI enables the “productization” of consulting knowledge. Demand for traditional strategy consulting is reportedly weakening as AI - enhanced analytics tools can process large datasets and generate insights that previously required human consultants (Bezuidenhout et al., 2023). AI tools are now used to map procurement processes, analyse employee contracts and diagnose operational inefficiencies, shifting revenue models from hourly billing to subscription-based access to analytical platforms (Bezuidenhout et al., 2023; Spring et al., 2022). The literature also notes increased competition from technology developers who, despite lacking formal professional accreditation, can deliver AI - driven services directly to clients (Bezuidenhout et al., 2023).

Overall, the evidence suggests that AI does not simply replace professionals but fundamentally changes how they work through a combination of automation and augmentation. AI systems “buffer” senior staff from low - value tasks, while chatbots and expert systems enable junior employees to handle routine claims with accuracy comparable to senior practitioners (Spring et al., 2022). However, a persistent challenge is the “black - box” nature of deep learning models, which makes it difficult for professionals to justify AI - generated recommendations to clients or regulators (Königstorfer and Thalmann, 2020; Yang et al., 2024b). Additionally, AI’s efficiency undermines the traditional billable hour model, pushing firms toward fixed fee or outcome-based pricing structures (Bezuidenhout et al., 2023). As a result, PSFs are increasingly transitioning from being “gatekeepers of knowledge” to becoming orchestrators of data - driven insight generation (Bezuidenhout et al., 2023).

Table 7. AI Applications in Professional Services

Professional/Service Sector	AI Application	Reference
Accounting Profession	RPA automates rule-based tasks (data entry, invoice processing, tax preparation), thus reducing manual workload, increasing speed and accuracy and lowering operational costs	Zhang et al., 2020
	AI enables full-population audit analysis instead of sampling, leading to 100% analysis of transactions and anomalies and fraud detection in real-time	Spring et al., 2022
Accounting Profession	Neuro-Linguistic Programming (NLP) interprets unstructured documents (contracts, board minutes) to identify compliance risks, thus improving risk detection and accelerating audit preparation	Zhang et al., 2020

Retail Sector	AI Application	Reference
Accounting Profession	Machine Learning (ML) tools flag unusual ledger entries using global datasets leading to enhanced fraud detection and improved audit reliability	Zhang et al., 2020
	Drones support physical audit procedures such as inventory verification, enabling real-time stock checks and increasing audit efficiency	Zhang et al., 2020
Legal Sector	NLP accelerates document review and due diligence, leading to thousands of documents being processed rapidly and reduction on review time from months to weeks	Spring et al., 2022
	Predictive analytics forecasts litigation outcomes, supporting legal strategy by analysing case law and judge behaviour	Bezuidenhout et al., 2023
	AI-based self-service tools allow clients to review simple contracts expanding access to legal services and reducing lawyer workload	Spring et al., 2022
	Blockchain enables smart contracts that execute automatically, reducing need for intermediaries and increasing transactional efficiency	Zhang et al., 2020
Consulting Firms	AI-enhanced analytics process large datasets and generate insights, automating tasks previously done by consultants and accelerating analysis	Bezuidenhout et al., 2023
Consulting Firms	AI maps procurement processes, analyses employee contracts, and diagnoses inefficiencies, improving operational transparency and supporting data-driven decision-making	Bezuidenhout et al., 2023; Spring et al., 2022
	NLP accelerates document review and due diligence, leading to thousands of documents being processed rapidly and reduction on review time from months to weeks	Spring et al., 2022

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Chapter 8
Artificial Intelligence vs Human: Complementary or Competitive?

8.1 Augmented Intelligence and Human-in-the-Loop (HITL) Models

The transition from viewing AI purely as an automation mechanism to understanding it as a partner in Augmented Intelligence and Human - in - the - Loop (HITL) systems mark a fundamental redefinition of work. The literature increasingly emphasizes that the future of AI is not human replacement but human - machine symbiosis, where AI amplifies human abilities while humans contribute contextual understanding, creativity and judgment, capabilities AI cannot replicate. The collaborative vision aligns closely with the principles of Industry 5.0, which prioritizes human - centric, sustainable and resilient production systems rather than efficiency alone (Poláková et al., 2023; Sun and Song, 2025).

A key shift in this paradigm is the movement from automation to augmentation. Automation replaces human labour in routine tasks, whereas augmentation enhances human cognition and performance. Research identifies four levels of human - AI proximity: working independently, supplementing one another, interdependence and finally a hybrid “centaur” model in which AI functions as an extension of human intelligence (Sowa et al., 2021). In this hybrid state, humans and AI achieve a synergistic effect, producing outcomes superior to what either could achieve alone (Fügener et al., 2022; Sowa et al., 2021). Contrary to narratives predicting mass automation, this model often frees humans to focus on areas where they retain a comparative advantage, complex perception, creativity and social interaction, while AI manages data - heavy and optimization-based tasks (Tyson and Zysman, 2022; Willcocks, 2020). For example, in managerial roles, AI acts as a “digital coworker” that handles administrative tasks, enabling managers to focus on strategic decision - making (Sowa et al., 2021). In creative industries, tools such as GANs function as co-creative partners, with humans providing conceptual direction and AI delivering rapid execution (Mahmud et al., 2024; Sun and Song, 2025).

This collaborative dynamic is operationalized through Human - in - the - Loop models, which integrate human expertise directly into the machine learning lifecycle to improve model accuracy and reduce training costs (Wu et al., 2022). HITL systems rely on different control structures. In Active Learning (System Control), AI queries a human “oracle” only when uncertain, reducing labelling effort while improving performance (Mosqueira-Rey et al., 2023). Interactive Machine Learning (Shared Control) involves iterative human feedback to guide feature selection or model behaviour (Mosqueira-Rey et al., 2023). In Machine Teaching (Human Control), domain experts explicitly encode their knowledge into the system, producing interpretable and debuggable models accessible even to non - technical users (Mosqueira-Rey et al., 2023).

Table 8. Human-in-the-Loop (HITL) Models

HITL Models	Human Role	How It Enhances AI	Reference
Active Learning (System Control)	The AI system queries a human "oracle" only when uncertain about a label or decision.	Reduced labelling effort: improves model accuracy by focusing human input where it matters most.	Mosqueira-Rey et al., 2023
Interactive Machine Learning (Shared Control)	Humans iteratively guide the model through feedback, influencing feature selection or model behaviour.	Produces more adaptive, user-aligned models; improves transparency and responsiveness	
Machine Teaching (Human Control)	Domain experts explicitly encode knowledge into the system, shaping rules and decision logic.	Creates interpretable, debuggable models accessible to non-technical users; enhances trust and explainability.	

Achieving true synergy requires bidirectional delegation, where tasks are dynamically assigned based on confidence levels. Research shows that AI systems can often recognize their own uncertainty more reliably than humans can identify their limitations, resulting in superior combined performance (Fügener et al., 2022). For example, in pathology, an AI system with a 7.5% error rate and a human expert with a 3.5% error rate achieved a combined error rate of only 0.5% when working together (Su et al., 2021). In high stakes fields such as public safety, AI processes large datasets to detect anomalies and delegates low confidence cases to human experts, creating a continuous learning loop (Zheng et al., 2017).

However, several challenges must be addressed to enable effective human - AI collaboration. Trust is essential; without Explainable AI (XAI) to address the “black box” problem, users are unlikely to rely on AI recommendations (Mosqueira-Rey et al., 2023; Retzlaff et al., 2024). As AI takes over technical tasks, the demand for human soft skills (critical thinking, emotional intelligence, cultural interpretation) grows significantly (Kumar, 2023; Poláková et al., 2023). Organizations must also ensure psychological safety by clearly communicating that AI is intended to augment, not replace, human workers and by providing training that helps employees feel in control of the technology (Arslan et al., 2022; Einola and Khoreva, 2023).

Ultimately, HITL models aim to move beyond merely “accurate” AI toward “useful” AI systems that are trustworthy, transparent and aligned with user needs (Mosqueira-Rey et al., 2023). The literature points toward a future of reciprocal evolution, where humans shape AI through teaching and elevates human work to higher levels of complexity. This suggests that the most productive path forward is not full automation, but the strategic pairing of human ingenuity with machine precision (Einola and Khoreva, 2023; Sowa et al., 2021).

8.2 Automation Risk and Job Displacement

While the previous section emphasized the collaborative potential of Augmented Intelligence, a substantial body of literature highlights the competitive tension between human labour and AI. This perspective shifts the discussion from partnership to substitution, focusing on automation risks, sector specific vulnerabilities and broader trend of labour market polarization.

A dominant framework for understanding this tension is Routine - Biased Technological Change (RBTC). Earlier automation waves replaced humans in routine physical tasks, but modern AI is described as “RBTC on steroids”, because it now automates both routine and increasingly non - routine cognitive tasks (Tyson and Zysman, 2022). AI is particularly effective at replacing low-level cognitive work that is repetitive, data intensive and requires minimal social interaction, such as insurance underwriting or basic administrative support (Tyson and Zysman, 2022). However, it remains less capable in tasks requiring complex reasoning, creativity or interpersonal skills (Tyson and Zysman, 2022). This shift has revived long standing anxieties about technological unemployment; just as industrial machinery displaced manual labour, AI now threatens knowledge workers, generating a “Luddite fear” among white collar professionals (Frank et al., 2019; Shen and Zhang, 2024). Some scholars also warn that AI may increase the fewer workers, potentially reducing labour’s share of national income (Shen and Zhang, 2024; Tyson and Zysman, 2022).

The effects of AI are highly uneven across industries, creating a divide between sectors facing significant displacement and those experiencing job growth. Manufacturing and retail are among the most vulnerable; one comparative study found job displacement rates of 45% in manufacturing and 35% in retail due to automation of routine tasks (Siti et al., 2025). This “machine replacement” strategy is particularly common in industrial firms seeking cost reductions and efficiency gains (Shen and Zhang, 2024). Even within the technology sector, concerns persist: 49% of IT professionals fear their roles may be replaced by AI, especially positions such as manual software testing, traditional network administration and basic IT support (Adepoju and Adepoju, 2025). At the same time, demand is rising for roles in AI governance and cybersecurity (Adepoju and Adepoju, 2025). In contrast, healthcare and education show higher rates of AI - driven job creation (50% and 60% respectively) because these fields rely heavily on human interaction and empathy, making AI more augmentative than substitutive (Siti et al., 2025; Tyson and Zysman, 2022).

A recurring theme is labor market polarization, where employment grows at the high and low ends of the skill spectrum while middle - skill jobs decline. Historically, automation has hollowed out middle - wage roles in manufacturing and office support, and AI is expected to intensify this pattern, contributing to stagnant wages for middle and low skill workers (Tyson and Zysman, 2022). AI - enabled platforms are also accelerating the rise of nonstandard employment in the gig economy (Tyson and Zysman, 2022). While flexible, this work often involves “ghost labour” (tasks performed by humans to fill gaps in automated systems) characterized by low pay, limited protections and minimal career progression (Tyson and Zysman, 2022; Willcocks, 2020). As a result, productivity gains from automation are not evenly distributed, contributing to widening income and wealth inequality (Tyson and Zysman, 2022).

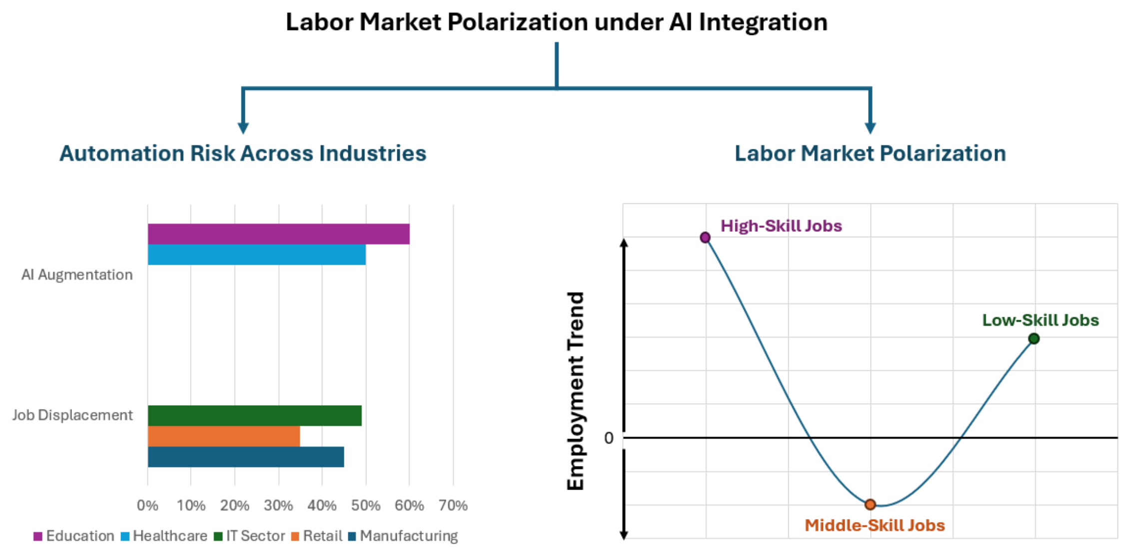

Figure 14. Labor Market Polarization under AI Integration. *AI adoption produces uneven effects across industries, with high displacement in manufacturing, retail, and parts of the IT sector, while healthcare and education experience net job creation due to the augmentative nature of AI. At the same time, AI intensifies labour market polarization: high-skill and low-skill roles expand, while middle-skill jobs decline, contributing to wage stagnation and widening inequality. Source: Created by the author based on literature review.*

This environment creates a paradox: AI generates demand for new skills while simultaneously eroding existing ones. Many workers lack the competencies required in AI integrated industries; one study found that 84% of respondents identified the AI skills gap as a major concern (Siti et al., 2025). Projections suggest that by 2025, 85 million jobs may be displaced while 97 million new roles emerge, underscoring the urgency of large-scale reskilling (Poláková et al., 2023). Yet evidence also shows that AI can lead to deskilling rather than upskilling. In a media consultancy case, employees reported that AI narrowed their responsibilities and made their work more technical rather than more strategic (Einola and Khoreva, 2023). Heavy reliance on AI risks eroding tacit knowledge and reducing workers' understanding of the broader context of their tasks (Einola and Khoreva, 2023). As technical tasks become automated, soft skills (critical thinking, communication, adaptability) become the primary source of human differentiation, though education systems often lag behind this shift (Poláková et al., 2023; Su et al., 2021).

Despite these risks, several studies challenge the idea of a catastrophic employment collapse. In the digital economy, traditional industrial clusters are evolving into virtual agglomerations, reducing geographical constraints and expanding labour markets (Shen and Zhang, 2024). Another argument is that the volume of work is increasing rapidly due to data growth and administrative complexity, meaning automation may be necessary simply to manage workloads rather than eliminate jobs (Willcocks, 2020). Evidence from China also suggests that AI can stimulate employment through capital deepening and expanded production; the adoption of industrial robots has been associated with increased labour demand due to the creation of new, more complex tasks (Shen and Zhang, 2024).

In summary, while fears of a “Robo - Apocalypse” may be overstated (Willcocks, 2020), the literature points to a challenging period of structural adjustment. The central risk is not the disappearance of work itself, but the disappearance of good work (Tyson and Zysman, 2022), marked by polarization, the erosion of middle - skill roles and an urgent need to reskill the workforce before displacement accelerates.

8.3 The Changing Nature of Work and New Skill Demands

The transformation of work reflects a broader shift from automation driven logic of Industry 4.0 to the human centric, resilient and sustainable principles of Industry 5.0 (Poláková et al., 2023; Sowa et al., 2021). As AI increasingly automates routine physical and cognitive tasks, the labour market is placing greater value on uniquely human capabilities, particularly creativity, emotional intelligence and advanced problem solving (Poláková et al., 2023; Su et al., 2021).

The shift has triggered a renewed emphasis on soft or transversal skills, which are becoming the core competencies of the future workforce because they are transferable and difficult for machines to imitate (Poláková et al., 2023). Evidence from job postings shows that demand for soft skills now exceeds demand for digital skills, even in technology - intensive fields such as IT and engineering, because employers prioritize adaptability, communication and collaboration in rapidly changing environments (Poláková et al., 2023). While technical skills such as programming languages have a short shelf life, soft skills like leadership, communication and interpersonal reliability are considered “evergreen”, remaining relevant despite technological change (S. Kumar et al., 2024). These skills are also essential for addressing the “last mile” of automation, where humans must handle complex, ambiguous or ethically sensitive tasks that AI cannot fully resolve (Willcocks, 2020).

At the centre of these evergreen competencies is creativity. Although AI excels at optimization and pattern recognition, it struggles with genuine novelty, artistic expression and conceptual ideation (Willcocks, 2020). Humans retain a comparative advantage in generating new ideas, while machines primarily support execution (Su et al., 2021). Creativity bridges analytical and intuitive thinking, enabling improvisation and innovation in ways that AI cannot replicate (Poláková et al., 2023). As a result, workplaces are moving toward co - creation, where humans act as creative directors and AI serve as a production tool. In advertising, for example, humans must interpret and refine AI - generated outputs into client - ready creative concepts, effectively shifting human work higher up the value chain (Einola and Khoreva, 2023). Because innovation depends on human creativity to generate new business models and products, creativity consistently ranks among the most critical skills for the future (Poláková et al., 2023).

Alongside creativity, Emotional Intelligence (EI) and social interaction are becoming indispensable. AI lacks the social and emotional understanding required for negotiation, persuasion and caregiving (Su et al., 2021; Willcocks, 2020). Jobs requiring high levels of interpersonal interaction are therefore less vulnerable to automation and are experiencing increased demand (Tyson and Zysman, 2022). AI cannot authentically empathize or interpret cultural nuances, making humans essential in fields such as healthcare and education, where emotional skills are central (Siti et al., 2025; Tyson and Zysman, 2022). Interpersonal communication remains the most frequently requested soft skill, as machines struggle with the strategic and empathetic dimensions of human dialogue (Poláková et al., 2023). EI is also crucial for maintaining psychological safety in hybrid teams, helping workers manage the stress of collaborating with AI systems (Arslan et al., 2022).

The modern workplace also demands advanced cognitive skills, particularly in complex, open ended problem solving. While Ai can solve structured problems within defined parameters, it lacks metaknowledge, the ability to recognize the limits of its own understanding. Humans must therefore know when to rely on AI and when to intervene (Fügener et al., 2022). As AI generate increasingly large volumes of predictions and insights, workers need strong critical thinking skills to evaluate outputs for accuracy, bias and ethical implications (Adepoju and Adepoju, 2025; Poláková et al., 2023). The ability to challenge machine recommendations and apply common sense reasoning remains essential (Kumar, 2023). Humans also excel at intuitive reasoning, enabling rapid decision - making in uncertain or dynamic environments, an area where AI still struggles (Zheng et al., 2017).

Ultimately, the literature suggests that the future of work depends on fusion skills, the ability to combine human strengths with AI capabilities (Einola and Khoreva, 2023). Workers must develop AI literacy to supervise AI tools, understand how to provide appropriate data, interpret outputs and correct errors (Einola and Khoreva, 2023). The rapid pace of technological change also requires learning agility, or the capacity to continuously unlearn and relearn digital tools (Kumar, 2023). Success increasingly relies on collaborative intelligence, where human - machine teams outperform either working alone, for example in pathology where hybrid collaboration reduced error rates by 85% compared to human only performance (Su et al., 2021).

In conclusion, the literature indicates that the primary challenge ahead is not a shortage of jobs, but a shortage of workers equipped with the right combination of technical fluency and high level cognitive, social and creative skills (Su et al., 2021; Willcocks, 2020). The real risk is a skills transition crisis, not a job quantity crisis, underscoring the urgency of preparing the workforce for these inimitable human capabilities (Willcocks, 2020).

Table 9. The Shift in Skills due to New Skill Demands.

Traditional Skill Focus	Emerging Skill Demand	Nature of the Shift	Reference
Technical digital skills limited to IT or engineering	Broad digital adaptability across all roles	Even tech-intensive fields now prioritize adaptability, communication, and collaboration in fast-changing environments.	Poláková et al., 2023
Basic interpersonal skills	Evergreen soft skills (leadership, communication, interpersonal reliability)	Essential for the “last mile” of automation where humans handle ambiguity, ethics, and complex judgement.	S. Kumar et al., 2024; Willcocks, 2020
Routine creativity (incremental problem-solving)	Advanced creativity and conceptual ideation	AI optimizes patterns but struggles with novelty, artistic expression, and conceptual thinking.	Willcocks, 2020

Traditional Skill Focus	Emerging Skill Demand	Nature of the Shift	Reference
General social interaction	Emotional Intelligence (EI) and high-touch interpersonal skills.	AI cannot negotiate, persuade, empathize, or interpret cultural nuance; human EI is critical in healthcare, education, and caregiving.	Su et al., 2021; Willcocks, 2020; Siti et al., 2025; Tyson and Zysman, 2022; Poláková et al., 2023; Arslan et al., 2022
Structured problem-solving	Advanced cognitive skills (critical thinking, metaknowledge, intuition)	Humans must evaluate AI outputs, detect bias, know when to override AI, and make rapid decisions in uncertainty.	Fügener et al., 2022; Adepoju & Adepoju, 2025; Poláková et al., 2023; Kumar, 2023; Zheng et al., 2017
Task execution separate from AI systems	Fusion skills (human-AI collaboration)	Workers combine human strengths with AI capabilities; requires AI literacy, learning agility, and collaborative intelligence.	Einola & Khoreva, 2023; Kumar, 2023; Su et al., 2021

8.4 Managing the Hybrid Workforce

Managing a hybrid workforce, where humans and AI work alongside, requires moving beyond the idea of AI as a simple efficiency tool. Instead, organizations must design symbiotic systems in which humans and AI function as coordinated teammates. To achieve this, firms need conceptual frameworks that clarify how humans and machines interact. One such model is the Proximity framework, which outlines four levels of human - AI collaboration and culminates in a hybrid “centaur” mode where AI acts as an extension of human cognition, enabling superior joint performance (Sowa et al., 2021). This conceptual foundation is operationalized through the HITL pipeline, which integrates human expertise into machine learning lifecycle via Active Learning, Interactive Machine Learning or Machine Teaching (Mosqueira-Rey et al., 2023). Building on this, Hybrid Augmented Intelligence Framework introduces a confidence-based loop: when AI’s confidence is low, it defers to a human, and the human’s decision is fed back into the system, creating a synergistic “1 + 1 > 2” effect (Zheng et al., 2017). At the same time, Paradox Theory highlights that automation and augmentation are not opposites but interdependent; employees often perform “ghost work”, such as data cleaning, that enables the very automation intended to reduce human labour (Einola and Khoreva, 2023; Willcocks, 2020).

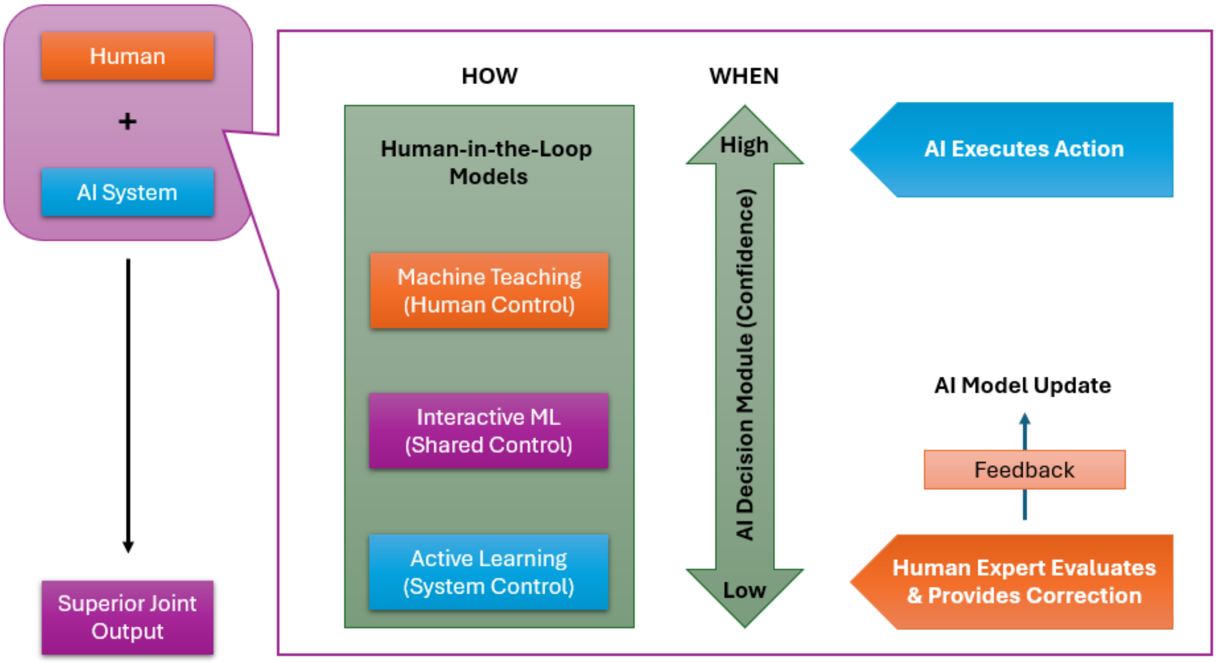

Figure 15. The Bidirectional Confidence-Based Delegation Loop. *Hybrid intelligence emerges when humans and AI operate in “centaur mode”, combining complementary strengths to achieve superior joint performance. This collaboration is operationalized through HITL pipelines which embed human expertise into the model lifecycle. Additionally, the confidence-based delegation loop enables dynamic task allocation: when AI confidence is high, it acts autonomously; on the other hand, it defers to a human expert. Human corrections are fed back into the system, creating a reinforcing cycle where humans and machines together achieve a “1+1>2” synergistic effect.* ***Source:*** *Created by the author based on literature review.*

Effective hybrid workforce management also requires clear strategies for task delegation. Research shows that humans are not always good at deciding when to rely on AI because they often lack “metaknowledge”, the ability to recognize their own limitations. As a result, hybrid performance improves when delegation is inverted, meaning the AI decides when to involve the human (Fügener et al., 2022). AI systems can be programmed to detect uncertainty thresholds and assign tasks, accordingly, reducing the risk of human overconfidence (Fügener et al., 2022). Managers must also ensure comparative advantage, based task allocation, where AI handles data heavy and optimization tasks, while humans focus on perception, creativity and social intelligence (Willcocks, 2020; Zheng et al., 2017). This shift requires new performance evaluation systems, as traditional metrics do not account for human limitations, such as fatigue or emotional variability, when working alongside tireless AI systems (Arslan et al., 2022).

A major barrier to hybrid integration is the trust gap and the psychological discomfort associated with working alongside algorithms. As AI evolves from a tool to a “junior colleague”, leaders must cultivate collaborative intelligence, where humans and AI enhance each other’s strengths (Arslan et al., 2022; Einola and Khoreva, 2023). Overcoming “algorithm aversion” and fears of job loss requires transparent communication about AI’s role, capabilities and limitations, helping employees feel secure and informed (Arslan et al., 2022). Implementing Explainable AI (XAI) is essential for building trust, as humans must be able to understand and audit AI decisions; however, organizations must balance transparency with the risk of overwhelming users with excessive detail (S. Kumar et al., 2024; Zheng et al., 2017).

Integrating AI into the workforce is fundamentally a change management challenge that requires assessing organizational readiness. The Technology - Organization - Environment (TOE) framework emphasizes that successful adoption depends not only on technological capability but also on organizational structure, culture, and regulatory context (Sun and Song, 2025). True readiness requires both financial resources and strong capabilities, such as fostering an innovation culture and involving employees in co - creating AI tools, an approach shown to increase acceptance and perceived control (Sowa et al., 2021; Sun and Song, 2025). This transition also demands extensive reskilling to close the AI skills gap and build a “fusion workforce” (Siti et al., 2025). Workers must continuously develop fusion skills, including AI literacy, metaknowledge and soft skills such as critical thinking, emotional intelligence a(Adepoju and Adepoju, 2025; Einola and Khoreva, 2023; Fügener et al., 2022; Poláková et al., 2023) et al., 2023).

In summary, managing a hybrid workforce requires a multifaceted strategy. Organisations must define the mode of collaboration and measure synergy (Sun and Song, 2025), implement inversion protocols that allow AI to delegate low - confidence tasks to humans (Fügener et al., 2022), invest in XAI to ensure transparency (Retzlaff et al., 2024), prioritize both technical and soft skill reskilling (Poláková et al., 2023) and redesign performance metrics to reflect the collaborative nature of human - AI work (Arslan et al., 2022).

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Chapter 9
Limitations, Challenges, and Future Directions

9.1 Key Challenges in Strategic AI Adoption

The rapid integration of AI across organizational functions introduces a series of challenges that directly affect the human element of work. As AI systems increasingly influence hiring, evaluation, decision - making and daily operations, firms must confront issues of algorithmic fairness, data privacy, explainability and intellectual property. These concerns highlight the tension between technological optimization and the preservation of human - centered management practices.

A major concern is algorithmic bias and fairness. Although AI is often promoted as a tool for reducing subjectivity in HR processes, research shows that algorithms can reproduce or even amplify historical inequalities embedded in training data. HR functions are therefore required to act as institutional entrepreneurs, redesigning workflows to support human - AI collaboration while managing risks such as discriminatory outcomes (Chowdhury et al., 2024, Huang et al., 2023). AI driver recruitment tools can standardise screening and reduce recency bias or favoritism in performance evaluations (Bhosale et al., 2022; Janiesch et al., 2021; Khogali and Mekid, 2023). High profile failures illustrate the risk: Amazon abandoned its AI recruiting tool after it learned to downgrade resumes containing the word “women’s” and Google’s Vision AI has been criticised for racially biased image labels (Enholm et al., 2022; Janiesch et al., 2021). Bias can also emerge through opaque correlations, such as filtering candidates based on zip codes or employment gaps, which may indirectly reflect socioeconomic or racial characteristics (Huang et al., 2023; Stone et al., 2024). Emotion - recognition and facial - analysis tools used in video interviews raise further concerns, as micro - expression analysis is often unreliable and may disadvantage individuals from diverse cultural backgrounds or those with disabilities (Stone et al., 2024; Vrontis et al., 2022).

These risks are compounded by the principle of “garbage in, garbage out”, which underscores that AI systems are only as reliable as the data on which they are trained. Inaccurate, incomplete or biased datasets inevitably produce flawed models, undermining strategic goals and potentially embedding systemic discrimination into organisational processes (Patil, 2025). As organisations increasingly rely on data driven decision making, ensuring data quality becomes a foundational ethical and operational requirement.

Closely linked to fairness is the “black box” problem, referring to the opacity of advanced AI models such as Deep Learning and Neural Networks. These systems often achieve high predictive accuracy but provide little insight into how decisions are made, creating significant barriers in regulated or high - stakes environments (Hossain et al., 2022; Saranya and Subhashini, 2023). In HR, this opacity complicates accountability for decisions such as candidate rejection or promotion denial, raising legal and ethical concerns about transparency and due process (Căvescu and Popescu, 2025; Enholm et al., 2022). The inability to explain AI - generated outcomes also contributes to organisational dehumanisation, where employees feel reduced to data points and may lead to skill decay as HR professionals become overly dependent on automated systems (Khogali and Mekid, 2023; Morandini et al., 2023). Similar challenges appear in other sectors: technicians may distrust predictive maintenance systems they cannot interpret (Khedr and Rani, 2024), healthcare professionals may hesitate to rely on opaque diagnostic models (Al Kuwaiti et al., 2023; Bekbolatova et al., 2024) and financial analysts may question the reliability of AI - generated recommendations (Königstorfer and Thalmann, 2020; Yang et al., 2024b). Without Explainable AI (XAI), trust in AI systems remains limited, undermining adoption and increasing legal exposure (Janiesch et al., 2021; Mosqueira-Rey et al., 2023; Retzlaff et al., 2024).

Another major challenge concerns data privacy and surveillance, particularly as IoT devices and Cyber - Physical Systems function as the “sensory nervous system” of modern organisations. These systems continuously collect data on employee behaviour, productivity, location and even biometric signals. While such data can optimise workflows, it also blurs the line between performance monitoring and intrusive surveillance. The increasing “datafication” of employees raises significant legal obligations under frameworks such as the General Data Protection Regulation (GDPR), which mandates transparency, proportionality and explicit consent in data processing (Enholm et al., 2022; Vrontis et al., 2022). Organisations must therefore balance operational efficiency with the protection of worker autonomy and privacy rights.

Collectively, these challenges underscore the need for robust governance frameworks that ensure fairness, transparency, accountability and respect for human dignity. As organisations increasingly rely on AI to support decision - making, the ethical and legal implications of these systems must be addressed proactively to maintain trust and uphold the principles of human centered management.

9.2 Limitations of the Current Study

Although this study reaches several important conclusions that are further discussed in Chapter 10, it also presents certain limitations. First, the research is based on a narrative literature review rather than empirical data collection. As a result, the findings depend on the availability, quality, and scope of existing academic sources. The absence of primary data restricts the ability to generalize conclusions across industries and organizational contexts.

In terms of scope, the study focuses on selected sectors, which means that other industries may be underrepresented. The analysis also prioritizes recent literature, potentially excluding older but still relevant foundational work. This choice enhances contemporary relevance but may limit historical depth.

Additionally, AI is a rapidly evolving field.Definitions, capabilities, and applications change quickly, which may render some insights time-sensitive. Moreover, the complementary versus competitive dynamic between humans and AI is highly context-dependent and may vary significantly across organizations, culture, and technological maturity levels. Data availability also poses constraints: some sectors have richer academic coverage than others, leading to uneven representations, while access to primary or industry-specific datasets was not possible, limiting insights into real-world implementation challenges.

From a technological and practical perspective, many AI tools and applications discussed in the study may evolve or become outdated, affecting the long-term relevance of the findings. The study does not include technical evaluation of AI models, algorithms, or performance metrics, and ethical, legal, and regulatory frameworks differ across countries, limiting the global generalizability of the conclusions.

Finally, the synthesis and interpretation of literature inherently involve subjective judgement. The study is written in English, which may exclude relevant non-English academic sources and introduce linguistic bias.

9.3 Future Research Directions

Looking ahead, several opportunities emerge for future research in this field. Firstly, upcoming studies could incorporate empirical data to validate the theoretical insights presented in this thesis. Cross-industry comparisons may reveal how AI adoption differs across sectors with varying levels of digital maturity, while longitudinal research could track how human-AI collaboration evolves over time.

In examining human-AI complementarity, further work is needed to identify the conditions under which AI enhances rather than competes with human capabilities. Future studies could explore how factors such as task complexity, uncertainty, or risk influence the optimal balance between human judgement and AI automation. Additionally, hybrid intelligence models and Human-in-the-Loop (HITL) frameworks should be tested in real organizational environments to better understand their practical implications. Since certain industries remain underexplored in the context of AI-driven competitive advantage, future research could also investigate how regulatory environments shape AI adoption in such sectors, while cross-country comparisons may highlight cultural or institutional differences in AI integration.

Further research is also needed on governance mechanisms that ensure fairness, transparency and accountability in AI systems. Scholars could examine how organizations operationalize ethical AI principles in everyday decision-making and assess the impact of emerging regulations, such as the European Union's AI Act and updated to the GDPR, on strategic AI deployment. Another important direction involves understanding how AI reshapes job roles, skill requirements, and organizational learning processes. This includes exploring effective reskilling and upskilling strategies for hybrid human-AI teams, as well as investigating the psychological and cultural dimensions of AI acceptance in the workplace.

Moreover, improving data quality and reducing bias in AI training datasets remains a critical area for future inquiry. Research could evaluate the effectiveness of Explainable AI (XAI) tools in increasing trust and adoption, while also examining how transparency influences managerial decision-making and employee perceptions of AI systems. Finally, future work could explore how AI reshapes traditional management frameworks, such as those analysed in this thesis, and investigate how firms can integrate AI into long-term strategic planning and innovation processes from the earliest stages.

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Chapter 10
Conclusion

10.1 Summary of Key Findings

The contemporary strategic landscape is undergoing a profound shift as organisations transition from traditional sources of competitive advantage toward capabilities rooted in data, intelligence and human - machine collaboration. Competitive advantage, historically grounded in unique strategic positioning and difficult to imitate resources (Assenshoh-Kodua, 2019; Hamadamin and Atan, 2019; Kuncoro and Suriani, 2018; Wang, 2013), is now increasingly shaped by internal firm characteristics that determine how effectively organisations can sense, interpret and respond to rapid technological change. In this environment, the VRIO framework is being actively reinterpreted: data superiority, algorithmic performance and human capital are emerging as dynamic VRIO assets whose value lies in accelerated innovation cycles and whose inimitability stems from recursive learning loops and path dependent talent development (Dzreke, 2024; Huang et al., 2023). The Knowledge - Based View reinforces this shift by positioning tacit expertise, practical wisdom and organisational learning as enduring sources of advantage in a world where data alone is insufficient (Assensoh-Kodua, 2019; Chowdhury et al., 2024; Cuthbertson and Furseth, 2022). Contemporary research converges on the idea that no single framework is adequate; firms must integrate traditional strategy tools with AI and Big Data analytics to enhance decision making speed and adaptability (Jowarder and Jowarder, 2025; Zhylinska and Gitko, 2025). As digital assets become increasingly perishable, sustainable advantage emerges not from possession but from the dynamic capability to reconfigure, renew and co - evolve with technological shifts.

Within this paradigm, Artificial Intelligence has become a strategic meta - capability. In practice, AI remains within the domain of Artificial Narrow Intelligence (ANI), excelling at specialised tasks within predefined boundaries (Rashid and Kausik, 2024; Riahi et al., 2021). From a Resource Based View perspective, AI is best understood not as a standalone asset, but as a composite organisational capability that integrates data, algorithms and human expertise (Peretz-Andersson et al., 2024). Because AI depends fundamentally on Big Data, its strategic value is inseparable from the data infrastructures that support learning and action (Goralski and Tan, 2020; Kumar et al., 2024). Achieving this requires a coordinated technological ecosystem: IoT provides sensory input, 5G enables real time communication, AI functions as the analytical core and Digital Twins offer simulation environments for risk free experimentation (Elahi et al., 2023; Ghosh et al., 2018). Blockchain adds a trust layer by ensuring data integrity and preventing malicious manipulation such as False Data injection (Amin et al., 2022; Mohammed et al., 2025). Strategic decisions regarding Generative AI (GenAI) further shape competitive outcomes. While off the shelf models offer speed, firms that customise foundation models with proprietary data avoid strategic convergence and build more defensible advantages (Dzreke, 2024; Kanbach et al., 2024; Wang et al., 2025). Ultimately, sustainable advantage in the GenAI era depends less on the models themselves and more on the governance structures, proprietary data pipelines and workflow integrations that determine how effectively AI is deployed (Dzreke, 2024; Gao et al., 2024; Jackson et al., 2024).

These capabilities are transforming business models across industries. AI enables Data - Driven Business Model Innovation (DDBM) and Digital Servization, shifting firms from selling products to selling outcomes and performance (Ghosh, 2025). AI - enabled offerings function as “living assets” that improve as they accumulate data, creating strong lock - in effects (Kanbach et al., 2024; Sjödin et al., 2023). In manufacturing, AI drives Industry 5.0 through intelligent robotics, Predictive Maintenance (PdM), autonomous agentic optimisation and continuous visibility into sustainability performance (Aylak, 2025; Sodiq Fowosere et al., 2025). In finance, AI strengthens competitive intelligence and security (Mahalakshmi et al., 2022; Yousaf et al., 2025), while healthcare grapples with the tension between diagnostic potential and risks related to bias and privacy (Al Kuwaiti et al., 2023; Bekbolatova et al., 2024). Retailers balance hyper personalisation with privacy concerns (Kumar and Koshy, 2025; Spring et al., 2022; Satish Krishnamurthy et al., 2024; Yousaf et al., 2025) and Professional Service Firms (PSFs) face a structural shift as AI automates routine claims, undermining billable hours and pushing firms toward roles as orchestrators of data driven insight generation (Bezuidenhout et al., 2023). Yet these sectors remain constrained by the “black box” challenge, which limits the ability to justify AI - generated recommendations to regulators (Königstorfer and Thalmann, 2020; Yang et al., 2024b).

Despite rapid automation, human capital remains the most enduring strategic asset. Applying Porter’s Five Forces to the labour market highlights the intensifying competition for scarce talent and the rising threat of AI substitutes (Anastasiu et al., 2020). Human capital sustains competitiveness by enabling innovation, creativity and navigation of uncertainty (Cuthbertson and Furseth, 2022). Consequently, HR has evolved into a strategic architect, leveraging AI to automate processes and generate insights (Nawaz et al., 2024) while cultivating a human - AI symbiosis in which machines handle analytical complexity and humans contribute empathy, contextual reasoning and creative judgment (Jaiswal et al., 2022). Managing this hybrid workforce requires defining synergy (Sun and Song, 2025), establishing inversion protocols that allow AI to delegate low confidence tasks to humans (Fügener et al., 2022), reskilling employees for emerging roles (Poláková et al., 2023) and redesigning performance metrics to reflect collaborative work (Arslan et al., 2022). The primary challenge ahead is not mass unemployment but a skill transition crisis (Willcocks, 2020). The real risk is the erosion of "good work" and the polarisation of labour markets if reskilling does not keep pace with technological change (Tyson and Zysman, 2022; Su et al., 2021). Organisations must guard against skill decay by ensuring employees retain the ability to perform tasks independently for effective Human - in - the - Loop oversight (Morandini et al., 2023; Mosqueira-Rey et al., 2023). HR must also mitigate the digital divide through inclusive training (Jaiswal et al., 2022) and invest in data stewardship roles to maintain data quality (Elahi et al., 2023; Nawaz et al., 2024). Ultimately, human - machine interaction represents a path of reciprocal evolution, pairing human ingenuity with machine precision (Einola and Khoreva, 2023; Sowa et al., 2021).

These opportunities are tempered by significant governance challenges. The principle of "garbage in, garbage out" remains a fundamental risk: flawed or biased data inevitably produce flawed models (Patil, 2025). Technical bottlenecks, talent shortages (Cao, 2018; Ghosh, 2025) and the persistent opacity of deep learning systems further complicate adoption (Hossain et al., 2022, Căvescu and Popescu, 2025; Enholm et al., 2022). AI integration also risks organisational dehumanisation (Khogali and Mekid, 2023) and raises deep privacy concerns requiring strict adherence to GDPR and similar frameworks (Enholm et al., 2022; Vrontis et al., 2022). To mitigate these risks, organisations must adopt proactive AI governance, including diverse development teams to reduce algorithmic blind spots (Enholm et al., 2022; Jorzik et al., 2024) and alignment with European Commission guidelines for Trustworthy AI (Enholm et al., 2022; Perifanis and Kitsios, 2023). Thus, human accountability must remain central to ensure responsible deployment (Chowdhury et al., 2024; Huang et al., 2023).

10.2 Contribution to Theory and Practice

This study offers several contributions to both theory and practice by synthesizing diverse perspectives on competitive advantage, technological transformation, and the evolving relationship between humans and Artificial Intelligence.

Theoretical Contributions

Theoretically, the thesis advances the understanding of competitive advantage in the age of AI by integrating traditional strategic management frameworks, such as the Resource-Based View, Dynamic Capabilities and the Knowledge-Based View, with contemporary developments in AI technologies. By examining how AI functions as both a strategic resource and a dynamic capability, the study highlights the shifting foundations of value creation and organizational performance.

A key theoretical contribution lies in clarifying the conditions under which AI acts as a complementary versus competitive force relative to human capabilities. Through the synthesis of literature across multiple sectors, the thesis demonstrates that the human-AI relationship is not binary but context-dependent, shaped by task characteristics, data availability, organizational maturity, and regulatory environments. This perspective enriches ongoing debates on automation, augmentation, and hybrid intelligence models.

Furthermore, the study contributes to emerging theoretical discourse on Human-in-the-Loop (HITL) systems and hybrid workforce structures. By connecting these concepts with strategic management theory, it provides a more holistic understanding of how organizations can balance autonomy, oversight, and collaboration between humans and intelligent systems.

Practical Contributions

From a practical standpoint, the thesis offers insights that can support managers, HR professionals and policymakers in navigating AI adoption. The analysis of sector-specific applications illustrates how AI can enhance efficiency, accuracy, and innovation across industries, while also identifying the risks associated with bias, opacity, and data privacy. These findings can guide organizations in designing responsible AI strategies that align with ethical and legal requirements.

The study also highlights the importance of workforce development in the transition toward hybrid human-AI collaboration. By identifying emerging skill demands and the need for continuous reskilling and upskilling, the thesis provides actionable implications for HR departments and learning and development initiatives. Additionally, the discussion of governance mechanisms underscore the necessity of transparency, accountability and fairness in AI-enabled decision-making.

Finally, the thesis offers practical guidance for integrating AI into long-term strategic planning. By demonstrating how AI reshapes traditional sources of competitive advantage, it encourages organizations to rethink their strategic priorities, invest in data quality and explainability, and adopt a more proactive approach to technological transformation.

10.3 Final Concluding Statement

In conclusion, AI models alone rarely generate sustainable competitive advantage. True differentiation arises when AI is rare through proprietary data, inimitable through deep workflow integration and organisationally supported through human - centric leadership and robust governance (Dzreke, 2024; Perifanis and Kitsios, 2023). Organisations that successfully combine technological intelligence with human insight, ethical stewardship and long - term sustainability objectives will be uniquely positioned to thrive in an era defined by relentless digital transformation.

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