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MASTER IN BUSINESS ADMINISTRATION

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THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE AS A STRATEGIC BUSINESS TOOL: CAPABILITIES, LIMITATIONS AND FUTURE PROSPECTS.

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The use of Generative Artificial Intelligence as a strategic business tool: Capabilities, limitations and future prospects.

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Abstract

Artificial Intelligence (AI) is one of the biggest trends of recent years, although its emergence dates back several decades. According to the Boston Consulting Group (2020) study, it is defined as “advanced forms of software that have the ability to imitate cognitive human capabilities and operate autonomously in various fields of activity”. Thus, it is clear that AI offers significant growth prospects and benefits, adding value to businesses.

Generative Artificial Intelligence (GenAI), as its main subcategory, has been rapidly evolving within the last decade and significantly altering how businesses approach strategic planning and decision-making. This thesis explores how GenAI can be used as a strategic business tool and is structured around three thematic axes.

Initially, it analyzes GenAI’s current capabilities and how it can be used to automate content creation, customize consumer experiences and improve innovation processes and operational efficiency by automating complex tasks.

Then, it identifies possible risks and limitations related to GenAI adoption, such as accuracy of the results, privacy of data, compliance with law, and ethical use of technology.

It also assesses GenAI’s long-term potential as a revolutionary strategic business tool and how it could change organizational structures and strategic planning procedures.

The study is based on the systematic literature review methodology, including articles published from 2015 to 2025, as well as case studies of firms that have integrated GenAI into their operations to achieve competitive advantage.

The conclusions of the paper give a balanced view on the practical advantages and disadvantages of GenAI in the strategic management domain by showing that GenAI promotes operational efficiency and strategic decision-making processes but should be compliant with legal and ethical regulations.

The study concludes with ideas and evidence-based recommendations for firms interested in adding GenAI software to their long-term strategy plans, while balancing innovation with operational and ethical concerns.

Keywords: Generative Artificial Intelligence, Machine Learning, Large Language Models, Strategic Management, Decision – Making, Competitive Advantage

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Η χρήση της Γενετικής Τεχνητής Νοημοσύνης ως εργαλείο επιχειρηματικής στρατηγικής: Δυνατότητες, περιορισμοί και προοπτικές.

Φανή Λαλιώτη

Περίληψη

Η Τεχνητή Νοημοσύνη (ΤΝ) αποτελεί μία από τις μεγαλύτερες τάσεις των τελευταίων ετών, αν και η εμφάνιση της χρονολογείται αρκετές δεκαετίες πριν. Σύμφωνα με μελέτη της Boston Consulting Group (2020) ορίζεται ως «προηγμένες μορφές λογισμικού που έχουν τη δυνατότητα να μιμούνται τις νοητικές ανθρώπινες ικανότητες και να λειτουργούν αυτόνομα σε διάφορους τομείς δραστηριότητας». Επομένως, είναι σαφές ότι η ΤΝ παρέχει σημαντικές προοπτικές ανάπτυξης και οφέλη, προσθέτοντας αξία στις επιχειρήσεις.

Η Γενετική Τεχνητή Νοημοσύνη (ΓΤΝ), ως κύρια υποκατηγορία της, έχει εξελιχθεί ραγδαία κατά την τελευταία δεκαετία και αλλάζει σημαντικά τον τρόπο με τον οποίο οι επιχειρήσεις προσεγγίζουν το στρατηγικό σχεδιασμό και τη λήψη αποφάσεων. Η παρούσα διπλωματική εργασία διερευνά πώς η ΓΤΝ μπορεί να χρησιμοποιηθεί ως ένα στρατηγικό επιχειρηματικό εργαλείο και δομείται γύρω από τρεις θεματικούς άξονες. Αρχικά, αναλύει τις τρέχουσες δυνατότητες της ΓΤΝ και πώς αυτή μπορεί να χρησιμοποιηθεί στην αυτοματοποίηση της δημιουργίας περιεχομένου, στην προσαρμογή των εμπειριών των καταναλωτών και στη βελτίωση των διαδικασιών καινοτομίας και της επιχειρησιακής αποτελεσματικότητας αυτοματοποιώντας πολύπλοκες εργασίες.

Στη συνέχεια, εντοπίζει πιθανούς κινδύνους και περιορισμούς που σχετίζονται με την υιοθέτηση της ΓΤΝ, όπως η ακρίβεια των αποτελεσμάτων, το απόρρητο των δεδομένων, η συμμόρφωση με τη νομοθεσία και η ηθική χρήση της τεχνολογίας.

Επίσης, αξιολογεί τις μακροπρόθεσμες δυνατότητες της ΓΤΝ ως ένα επαναστατικό στρατηγικό επιχειρηματικό εργαλείο και πώς θα μπορούσε να αλλάξει τις οργανωτικές δομές και τις διαδικασίες στρατηγικού σχεδιασμού.

Η μελέτη βασίζεται στη μεθοδολογία της συστηματικής ανασκόπησης βιβλιογραφίας, συμπεριλαμβάνοντας άρθρα που δημοσιεύτηκαν από το 2015 έως το 2025, καθώς και μελέτες περιπτώσεων από εταιρείες που έχουν ενσωματώσει την ΓΤΝ στις λειτουργίες τους για να επιτύχουν ανταγωνιστικό πλεονέκτημα.

Τα συμπεράσματα της εργασίας παρέχουν μια ισορροπημένη άποψη σχετικά με τα πλεονεκτήματα και τα μειονεκτήματα της ΓΤΝ στον τομέα της στρατηγικής διοίκησης, δείχνοντας ότι η ΓΤΝ προωθεί την επιχειρησιακή αποτελεσματικότητα και τις διαδικασίες λήψης στρατηγικών αποφάσεων αλλά πρέπει να είναι σύμφωνη με τους νομικούς και ηθικούς κανονισμούς.

Η μελέτη καταλήγει σε ιδέες και τεκμηριωμένες προτάσεις για επιχειρήσεις που ενδιαφέρονται να ενσωματώσουν λογισμικά ΓΤΝ στα μακροπρόθεσμα στρατηγικά τους σχέδια, εξισορροπώντας την καινοτομία με λειτουργικούς και ηθικούς προβληματισμούς.

Λέξεις – Κλειδιά: Γενετική Τεχνητή Νοημοσύνη, Μηχανική Μάθηση, Μεγάλα Γλωσσικά Μοντέλα, Στρατηγική Διοίκηση, Λήψη Αποφάσεων, Ανταγωνιστικό Πλεονέκτημα

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List of Abbreviations & Acronyms

ΓΤΝ	Γενετική Τεχνητή Νοημοσύνη
ΤΝ	Τεχνητή Νοημοσύνη
AI	Artificial Intelligence
BCG	Boston Consulting Group
CRM	Customer Relationship Management
DL	Deep Learning
DNN	Deep Neural Network
ERP	Enterprise Resource Planning
GDPR	General Data Protection Regulation
GenAI	Generative Artificial Intelligence
GPT	Generative Pre-trained Transformer
HR	Human Resources
IoT	Internet of Things
KPIs	Key Performance Indicators
LLMs	Large Language Models
ML	Machine Learning
NLP	Natural Language Processing
NPS	Net Promoter Score
PESTEL	Political, Economic, Social, Technological, Environmental, Legal
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RAG	Retrieval-Augmented Generation
RBV	Resource Based View
SLR	Systematic Literature Review
SMEs	Small and Medium-sized Enterprises
SWOT	Strengths, Weaknesses, Opportunities, Threats
VRIN	Valuable, Rare, Inimitable, Non-substitutable
VRIO	Value, Rarity, Imitability, Organization

1. Introduction

1.1 Background to Study

In recent years, business sector has experienced a groundbreaking transformation, as new digital technologies have emerged and changed the landscape. Among these, Artificial Intelligence (AI) and its many applications play crucial role in formulating a new way of life, altering the way organizations operate, decide and interact with their customers. AI relates to the field of computer science and engineering of designing and implementing programmes that imitate human intelligence, such as learning, reasoning, problem-solving and decision-making (McCarthy, 2007). It was first introduced in 1950s, but the rapid advancement of Big Data technologies within the last decade, such as excessive computer storage capabilities and high speed in data processing, empowered it with the availability and capabilities of Big Data (Duan et al., 2019). From automating daily repetitive tasks to making complex decisions, the options that AI offers can lead us to a multitude of directions and choices. Considering its ongoing evolvement, its integration across various industries creates significant opportunities for improved efficiency, innovation and long-term competitive advantage.

Being part of the broader category of AI, Generative Artificial Intelligence (GenAI) moves beyond simple data analysis, as it uses deep learning algorithms to analyze complex patterns and generate new content based on whatever is requested to do. GenAI models learn those patterns and structure from examples they find in emails, texts and images, and then generate new examples that are similar. The ability to produce new and original outputs makes GenAI not just a computer programme, but a strategic asset that improves organizational decision-making, creativity, and innovation.

Traditionally, strategic decisions rely upon historical data, rational analysis and experience. However, most organizations fail to process numerous data in short timeframes, keeping up with the constant changes in market conditions. That is why GenAI adoption is important, as it boosts human intelligence using technologies like machine learning (ML), predictive analytics, and natural language processing (NLP), which analyze big data and produce more accurate insights in a shorter period of time, so that managers can make more informed and evidence-based decisions instead of basing only on their personal intuition (Asiabar, 2024).

Moreover, the acceleration by the pandemic of digital era causes inevitably integration of the latest technologies, like GenAI, in all business functions, emphasizing the shift from traditional strategic models to more agile, technology-driven ones (Kaggwa et al., 2024). Organizations that successfully adopt and implement these technologies are often better prepared to adapt to changes in their environment.

However, despite the rapid adoption of GenAI technologies, existing literature examines the technical applications of GenAI, while limited research integrates GenAI within strategic management frameworks such as Resource Based View (RBV), Dynamic Capabilities and sustainable competitive advantage. Thus, the gap in understanding the ways that GenAI can be effectively integrated into strategic management context creates a need for investigating its potentials and limitations. This study addresses this gap by synthesizing strategic, technological and governance perspectives.

As a result, the importance of exploring the role of GenAI in strategic management cannot be overstated, as it helps us understand how technology contributes to strategic decision-making, organizational innovation and competitive advantage.

1.2 Research Purpose and Objectives

This study explores the role of GenAI as a strategic business tool for modern businesses focusing on its potentials towards strategic management enhancement, as well as identifying the risks and limitations arising from its adoption.

Specifically, the research aims to understand the basic concepts of GenAI and strategic management, including GenAI's definition, its main applications in businesses and the strategic management principles. This understanding is important in order to analyze how GenAI improves decision-making, supports strategic innovation and creates competitive advantage.

The study also discusses risks and limitations associated with GenAI adoption, such as reliance on training data, absence of creativity, data biases, accuracy concerns, the need for supervision and compliance with regulations and legal frameworks.

For this purpose, the study sets the following objectives:

- To explore the key capabilities of GenAI within businesses, such as productivity increase through process automation, innovation promotion by developing new products and services and improved decision-making by analyzing large volumes of data, that results in better informed strategies and advanced outcomes.

- To identify risks, limitations and legal, ethical and operational challenges that could affect the effective use of GenAI in strategic planning.
- To develop a framework for successful implementation of GenAI in business strategies development, organizational processes and competitive positioning in the market.

By addressing these objectives, the study aims to provide evidence-based insights and recommendations on how businesses can use GenAI effectively. At the same time, it offers a balanced view of GenAI capabilities and limitations, and emphasizes the importance of following legal, ethical and operational guidelines for a responsible and effective integration into business strategies. Besides, it aims to contribute to the literature by highlighting the future prospects of GenAI and suggesting directions for further practice and research.

1.3 Research Questions

This thesis aims to answer the following research questions, which highlight both the opportunities and challenges associated with the use of GenAI as a strategic business tool:

- RQ1: What are the strategic capabilities of GenAI for modern businesses?
- RQ2: What are the technological limitations that affect the reliability and adoption of GenAI in strategic processes?
- RQ3: What are the legal, ethical and operational risks that arise from integrating GenAI into businesses and how they can be addressed?
- RQ4: What are the future prospects for the effective strategic integration of GenAI into businesses?

1.4 Research Methodology

The research is based on secondary analysis through a systematic literature review, which allows a comprehensive assessment of existing knowledge regarding the capabilities, limitations and prospects of GenAI. Scientific articles, case studies, reports from international organizations and relevant literature from 2015 to 2025 are utilized through official databases, such as Google Scholar, Web of Science, ScienceDirect and IEEE Xplore.

Selected articles are classified and analyzed based on the four research questions:

- the strategic capabilities of GenAI
- the technological limitations
- the legal, ethical and operational risks
- the future prospects for its effective strategic use

This way, we get an overall view that answers the research questions of the study.

1.5 Significance and Contribution of the Study

GenAI is indisputably one of the most exciting technological advancements, and within the last years has been already integrated into a multitude of business functions, such as content creation, process automation and productivity enhancement. However, we need to understand how it helps businesses to develop strategies and create and maintain competitive advantage in the market. Most studies are limited to the technical capabilities and business applications of GenAI with little research on its role as a long-term strategic management tool that affects competitiveness, decision-making and innovation processes. Thus, this study is of particular importance, as it fills the gap in literature and provides a comprehensive analysis of GenAI's capabilities, limitations and prospects.

At theoretical level, the study connects strategic management theories, such as RBV, Dynamic Capabilities, Porter's Five Forces Model and PESTEL framework, with the technological developments of GenAI and gives insights on how it can be used as a strategic tool, add value to businesses and achieve competitive advantage.

At practical level, the study sets directions for managers and business executives, so they have a clear view of the opportunities and risks associated with the integration of GenAI into their business strategies and operate within responsible strategic frameworks.

Overall, the research records the existing knowledge through systematic literature review, helps to understand the strategic value, risks and evolving capabilities of GenAI and contributes to the formulation of practical guidelines, in which GenAI can be effectively integrated into business corporations.

1.6 Structure of the Dissertation

The dissertation is structured into five main parts, which present the theoretical background, methodology, findings and conclusions arising from the systematic literature review on GenAI and its role in strategic management.

First chapter refers to the digital transformation in business sector due to the emergence of new technologies. It analyzes that GenAI is useful in strategic management, offering new opportunities for efficiency, innovation and competitive advantage, since traditional strategic methods cannot handle the amount and the acceleration of modern data. However, businesses lack knowledge in effective integration of GenAI into their strategies. Therefore, it is important to investigate the potentials, limitations, and prospects of GenAI in formulating business strategies. Besides, it describes the research objectives, the research questions and the methodology used in the study. At the same time, the significance and the contribution of the research, both on theoretical and practical level is analyzed, as well as the overall structure that follows.

Second chapter presents a review of relevant literature focusing on the evolution of GenAI and its applications across different business functions. It examines how GenAI technologies are integrated into areas, such as marketing, operations, human resources, finance, and of course research and development, while also exploring their strategic implications through established management theories, including the Resource-Based View and Dynamic Capabilities.

Third chapter analyzes the research methodology, that is based on a systematic literature review approach. It explains the data collection process, including the selection of databases, the keywords, and time horizon, as well as the inclusion and exclusion criteria used to ensure the relevance and quality of the selected sources. Besides, it refers to the process of article selection following PRISMA, the method of coding and thematic analysis procedures and, lastly, the analytical framework used to answer the research questions.

Fourth chapter analyzes the selected literature's results. It presents descriptive and thematic findings on GenAI's strategic capabilities, technical limits, and legal, ethical, and operational risks. It also discusses how GenAI creates sustainable competitive advantage and provides a conceptual framework that integrates inputs, capabilities, outcomes, risks, and governance mechanisms. Overall, it gives a balanced view of GenAI's strategic business opportunities and challenges.

Fifth chapter summarizes the key findings and answers the research questions of the study. It discusses the theoretical contribution of this thesis, in particular in relation to strategic management theories, and provides practical strategic recommendations for organizations aiming to successfully implement GenAI. It also discusses the limitations of the research and set directions for future studies. Finally, this chapter concludes that the long-term value of GenAI is not in the technology itself, but in its strategic integration, governance, and alignment with organizational capabilities, and that GenAI can become a vital part of future business strategy.

2. Literature Review

2.1 Artificial Intelligence in Business

2.1.1 Artificial Intelligence Definition and Structure

Before analyzing the ways that Artificial Intelligence (AI) technologies are influencing the business sector, we need to provide a definition of the term for a better understanding of the subject.

In 2007, John McCarthy, one of the founders of AI, described AI as "the science and engineering of making intelligent machines, especially intelligent computer programs" (McCarthy, 2007). Historical researches define AI in various ways, creating four basic approaches (Tripathi, 2023):

First, the Turing test approach proposed by Alan Turing in 1950, according to which a machine acts humanly. The test describes a human judge who asks questions to another person and a machine through a screen blindly. If the judge cannot identify the machine from the replies he receives, then the machine passes the test (Park, 2018). Figure 1 below represents the Turing test, where a human evaluator communicates with a computer and another human and needs to identify who is the human and who is the machine. If the computer cannot be identified as machine, then it is considered that it acts like a human and passes the test.

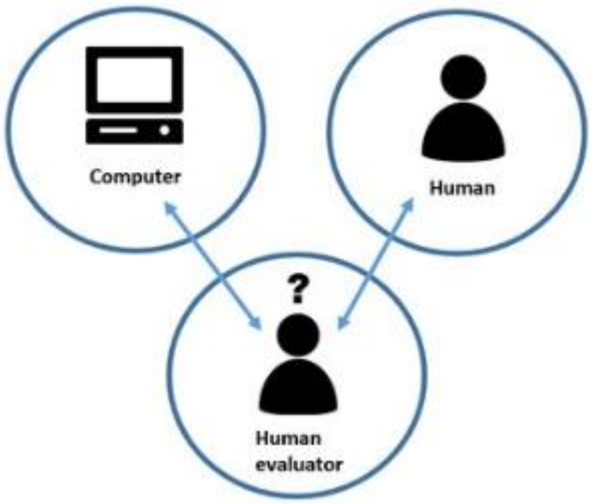

Figure 1 - Turing Test diagram. Source: Rebelo et al. (2022), ResearchGate.

Second, the cognitive modeling approach according to which a machine thinks humanly after being modelized with algorithms that simulate human problem-solving and mental processing through three theory methods, as shown in Figure 2:

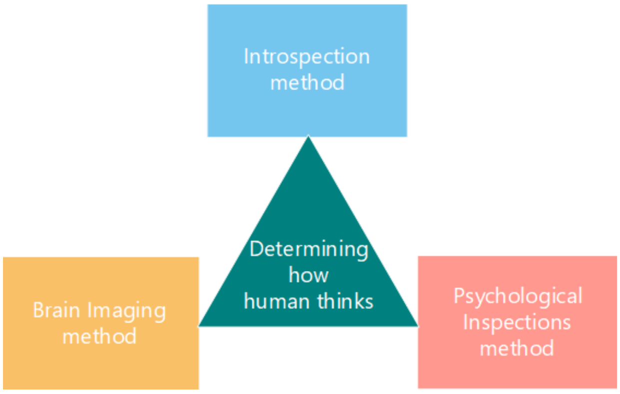

Figure 2 - Cognitive Modeling diagram. Source: Gopi Chandrakesan (2021).

- Through introspection method by examining our thoughts and seeing how it flows.
- Through psychological inspections method by observing a person in action.
- Through brain imaging method by observing the brain in action.

Converting the above methods into a computer programme allows that parts of the programme are thinking like the human brain (Russell & Norvig, 2021).

Third, the laws of "thought approach" according to which a machine thinks rationally based on the principles of common logic and a set of predefined rules and conditions that lead to correct conclusions (Russell & Norvig, 2021).

Fourth, the rational agent approach according to which a machine acts rationally based, not only on the principles of common logic and a set of rules that lead to correct conclusions, but also on probability theory that allows deciding under uncertain situations and adapting to changing environments (Russell & Norvig, 2021).

It seems that the rational agent approach is the most prevalent one, through which AI is related to rational computer agents that "operate autonomously, perceive their environment, adapt to changes, and create and pursue goals, so as to achieve the best outcome or, when there is uncertainty, the best expected outcome" (Russell & Norvig, 2021).

While AI is described in general “as the ability of a system to accurately interpret external data, to learn from those data, and to apply the acquired knowledge to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019), its definition is quite broad and includes a variety of advanced technologies, such as machine learning, deep learning, deep neural networks and natural language processing, which are the foundation of AI within a larger context.

Machine Learning (ML) is the branch of computer science related to statistics and the core of an AI system capable of learning through patterns and making automatically robust predictions from complex data (Taddy, 2018). This process is completed into two stages, as shown in Figure 3: first, the training stage, where models are trained on existing data in order to identify relationships and patterns, and second, the testing or decision – making stage, where the developed trained models are tested for determining the results of unknown datasets and support predictions and decision-making processes (Chauhan & Singh, 2018, Pandey et al., 2019).

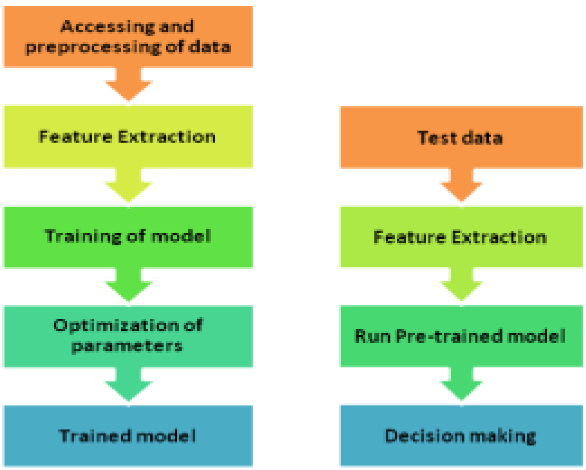

Figure 3 - Machine Learning stages. Source: Pandey et al. (2019), Google Scholar.

In business environments, ML technologies support organizations in improving decision-making, increasing efficiency though process automation and responding effectively to changing market conditions through trend forecasting (Chalmers et al., 2020). The latest generation of ML algorithms give the best possible outcome when process large amounts of data, increasing the level of automation in implementing prediction models (Taddy, 2018).

However, data increase does not necessarily imply that learning improves, as ML algorithms are limited by bias in the algorithm (when the selected algorithm is not suitable for a given task) and bias in the data (when the training data are generated by humans and represent their cognitive bias), which can lead to skewed predictions (Bzdok et al., 2017, Azaria, 2023, Mavrogiorgos et al., 2024).

Deep Learning (DL) is an advanced subset of ML influenced by biology, as it is based on deep neural networks (DNNs) that imitate the neurons of human brain and enables AI systems to identify complex patterns within large volumes of structured and unstructured data and develop highly accurate predictions. In business environments, DL technologies support applications such as predictive analytics, customer personalization, fraud detection and strategic forecasting. Their ability to process large datasets quickly enhances organizational decision-making and operational efficiency, making them strategically important for companies operating in dynamic and data-driven markets (Taddy, 2018, Chalmers et al., 2020). Figure 4 shows the multilayered information processing that a DNN allows in order to identify patterns and produce advanced analytical outcomes.

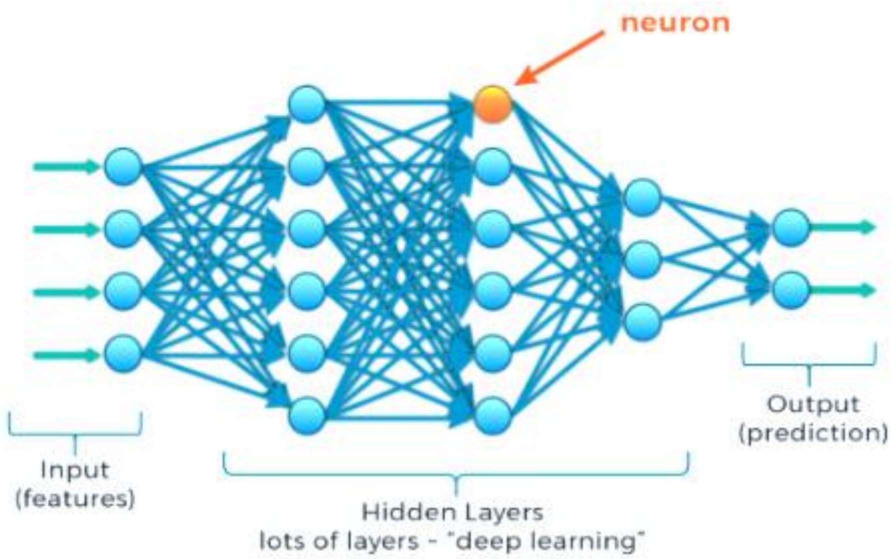

Figure 4 – DNN in Deep Learning. Source: Manika (2024), ProjectPro.

Natural Language Processing (NLP) is a subfield of computer science that helps machines to understand and use human language through mathematical modeling and computational techniques (Reshamwala et al., 2013) by analyzing the grammatical structure of sentences and the meaning of individual words, interpreting that meaning through algorithms and finally, producing outputs (Ali & Shandilya, 2021). NLP is used in both written and oral speech and is important for businesses that handle large volumes of unstructured text, such as emails, online chats and social media conversations, because it helps analyze and interpret the information automatically. Typical examples of NLP are chatbots and virtual assistants, like Siri and Google Assistant, which are used as automated question-answering systems that understand human language and deliver appropriate replies (Chandrika, 2024).

As the new technology era created advanced applications and software systems and paved the path for AI implementation and usage, the meaning of AI and its subfields are continuously evolving, offering the opportunity to enjoy the benefits of the fourth industrial revolution.

2.1.2 Artificial Intelligence Integration in Business Environments: Capabilities and Challenges

AI is part of a wider process known as the fourth industrial revolution, industry 4.0 or digital transformation, which was first introduced by the German government in 2011 and describes a significant shift towards advanced industrial technologies that support economic growth and high quality of life (Grandinetti, 2020, Hollebeek et al., 2021). Industry 4.0 is strongly connected to supply chain management, covering all stages from production to the customer, where clear and effective communication is necessary. As many industries handle large volumes of communication, AI helps them to better identify customer needs by analyzing social media and other online content and provide personalized products and services influencing customer choices and offering new insights that can drive business development (Mah et al., 2022, Chalmers et al., 2020).

AI combined with emerging technologies, such as Big Data, Blockchain and Internet of Things (IoT), completes operations and tasks that outperform humans in terms of speed and relevance, as it has the ability to identify patterns or details in data that are imperceptible to humans, leading to entrepreneurial opportunities across many industries and providing them with the necessary tools to invent new business processes and models (Peyravi et al., 2020, Chalmers et al., 2020). In the framework of IoT, AI is essential for processing and interpreting large volumes of data, facilitating the interconnection of software languages used by IoT devices (Ahmad et al., 2021). Within Blockchain technology framework, it provides a secure and transparent way to record digital transactions, ensuring the reliability and integrity of the results (Treiblmaier, 2018). This technology fusion is transforming technological entrepreneurship and reshaping the way new businesses are designed and developed (Elia et al., 2020).

There are several applications for AI in businesses, most of which aim at driving growth. When viewed as a major growth factor, AI allows organizations to increase the efficiency of operations, maintenance, and supply chains by anticipating, for instance, the required time for products to be transferred through the supply chain and predicting the material and shipping costs (Bharadiya et al., 2023). It also enhances customer experience by automating customer service processes through chatbots, improving products and services and introducing new features. It enables rapid and automated adaptation to changing market conditions by shifting business models from traditional manual changes to self-adjusting systems. It optimizes the balance between supply and demand through improved forecasting and planning capabilities, it identifies fraud in banking and finance sectors by detecting unusual patterns, and it enhances sales processes by predicting market trends and managing inventory through accurate data analysis (Wamba-Taguimdje et al., 2020).

In fact, AI fosters creativity and innovation in problem-solving and plays crucial role in strategic decision-making, as it applies in various leadership strategies. It is not only beneficial in cost leadership strategies, where the goal is process automation to minimize costs, but also in quality and relationship leadership strategies, which respectively aim to deliver superior customer experience and focus on building close bonds with customers to enhance satisfaction (Huang & Rust, 2021). Businesses provide value to customers through three stages: creation, delivery and interaction. In the creation stage, the goal is to create value for the customer. Through deep learning algorithms, companies may use predictive analytics to identify customer preferences, computational analytics to develop services, and pattern recognition technologies to identify and serve similar customer segments (Huang & Rust, 2021). In the delivery stage, emphasis is given on efficiency through automating repetitive tasks, such as shipping, delivery and payment processes, that minimize costs and facilitate the effectiveness and convenience of services. The interaction stage focuses on communication with customers and can be divided into marketing communication and post-purchase services, each of which requires advanced AI technologies capable of accurately recognizing and responding to human emotions (Huang & Rust, 2021).

AI not only helps businesses develop new capabilities and increase their flexibility, but its predictive power also supports the training and continuous improvement of business operations (Schrettenbrunner, 2020). In terms of improving services, it enhances their availability, supports the customer journey through real-time information, proactively handles multiple customers at once, and reduces waiting times and human intervention, allowing staff to focus on more complex tasks (Ameen et al., 2021, Costa et al., 2019).

In general, when integrated into business environments, AI is positively impacting on four different phases of the business process (Schrettenbrunner, 2020):

- On the opportunity recognition phase, where it empowers entrepreneurs to explore new possibilities.
- On the decision-making phase, where it allows for improved forecasting and determination.
- On the performance phase, where it improves the productivity of the business.
- On the education and research field, where it helps to accelerate and bridge the gap between theory and practice.

However, AI integration into businesses falls into some challenges, as it creates need for specialized staff, so that companies have to employ AI experts in key job positions to implement complex AI technologies, offering high salaries to attract and retain them (Schrettenbrunner, 2020). On the other hand, the cost of purchasing the required infrastructure for its implementation, including software, maintenance and data management costs, is high. Thus, the financial investment in AI is significant and not all companies, especially small ones, can afford it (Mogaji et al., 2020).

Besides, data collection processes can cause ethical concerns to customers related to manipulation and privacy, who need to be informed about how their data is being processed and give their consent, while companies are expected to manage and use this data with responsibility and assure customers that their information will remain anonymous and not be sold (Ameen et al., 2021, Mogaji et al., 2020).

Furthermore, the decreased level of human interaction within AI technologies can lead to negative customer experiences, if not managed properly (Ameen et al., 2021). Customers remain cautious towards AI use in tasks that require intuition or emotional involvement, or those that could lead to significant consequences, as they perceive AI bots unable to feel or less empathetic or unable to identify what is unique for each customer (Davenport et al., 2019).

Ultimately, while AI enhances human intelligence and improves service delivery capabilities, it is unlikely to fully replace human roles that require creativity, intuition and emotional understanding (Davenport et al., 2019). The integration of AI can significantly transform businesses; however, it must be implemented in a thoughtful and ethical way, in order to maximize its benefits and minimize its potential disadvantages (Gonçalves et al., 2022).

2.2 Generative Artificial Intelligence: Concepts and Tools

Figure 5 illustrates the interconnection among core technical concepts in the domain of AI.

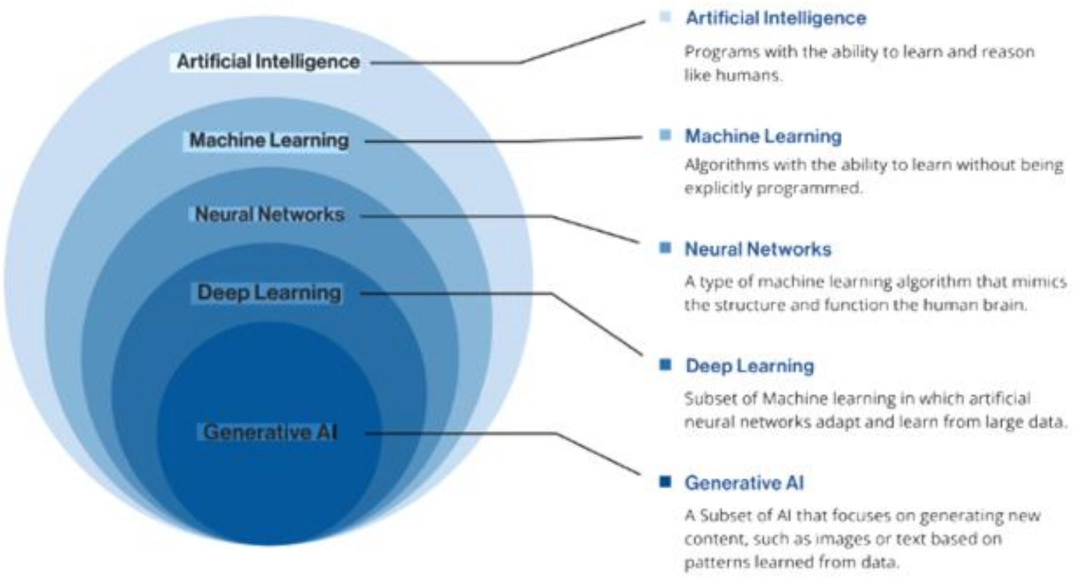

Figure 5 – AI Model Types. Source: Hartman (2025), Infoworks.

While AI has become increasingly popular in recent years, Generative Artificial Intelligence (GenAI), as its subset, experienced rapid growth in late 2022. According to the terminology, the word “generative” describes the ability to produce or create something. By this definition, all AI models can be technically considered as generative because they create outputs. However, not all AI-generated content is considered GenAI (Penalvo & Ingelmo, 2023).

In fact, GenAI refers to AI software systems that leverage machine learning and deep learning algorithms to create innovative output, like text, images, or other media, that users can engage with rather than numerical predictions, based on patterns learned from training on large datasets (Hartman, 2025). Unlike conventional AI, which typically focuses on tasks like classification, prediction, or decision-making, GenAI models are designed to learn and reproduce the underlying patterns and distribution in data (Yang et al., 2025). They are also particularly good at creating examples with modifications based on a prompt, such as answering a question, summarizing text or modifying the style of an image or document.

As the first concept of GenAI, prompt is an instruction, query or command that a user submits into a GenAI interface to request a response from the system, and its structure typically includes the role and background information, the core task, the desired format and the desired style of the output (Yang et al., 2024). An example of the basic structure of a prompt could be the following: "As a marketing expert (role), create a social media campaign (task) about the nutrition benefits of our new cereal product in a list with bullet points (format) in an accessible and enthusiastic tone (style)".

Effective prompts base on prompt engineering, which is the second concept of GenAI and relates to the process of designing and refining inputs for GenAI tools to achieve optimal outputs (Yang et al., 2024).

Another concept is tokenization, where input data are broken down into smaller parts called tokens, such as words, subwords or even characters, so GenAI tools learn relationship between words and understand human language (Hartman, 2025). In the phrase "Artificial Intelligence" or in the abbreviation "AI" for instance, each word and each character can be considered as a token.

The fourth concept of GenAI is embeddings, which are numerical representations of words that help GenAI models to understand the context and find similarities and differences in meaning between different texts by converting them into vectors. Words with similar meaning have vectors that are close to each other. For instance, the words "house" and "home" have similar embeddings and close vectors, while "apple" (the fruit) and "Apple" (the company) have different embeddings and distant vectors based on context (Hartman, 2025).

Vectors are stored in vector databases, which constitute the fifth and last concept of GenAI, and provide the ability to accurately locate and retrieve data based on vector similarity. This enables searches based on semantic or contextual relevance instead of depending only on exact matches or predefined rules (Hartman, 2025).

The most commonly used type of GenAI for text is Large Language Models (LLMs), which are data transformation systems trained on large numbers of parameters that understand and generate human-like text by predicting which words are most likely to come next based on probabilities (Yang et al., 2024). For example, if the first word of a sentence is "they," there is a higher probability that the next word is "are" rather than "is" (Kalota, 2024). LLMs are based on transformer models, which are types of artificial neural network that process data through an encoder and generate output through a decoder, which may be in a different format (Kalota, 2024). For example, a transformer can receive a text prompt and generate an essay, image, or audio (Kalota, 2024). Chatbots and virtual assistants are typical applications of GenAI and LLMs.

A specific type of transformer model is Generative Pre-trained Transformer (GPT) model, which uses only the decoder part and generates sequences of words, code, or other data in response to an input prompt, with ChatGPT being the most popular one (Kalota, 2024). Developed by OpenAI and introduced in November 2022, ChatGPT is a chatbot that leverages AI, NLP, and LLMs to communicate with its users by answering questions and providing human-like responses (Kalota, 2024). This programme can generate unique articles about any topic by searching for information online and using strong grammar and writing skills. On demand, it can generate basic computer code, simple financial analysis, essays on almost any subject, summaries of technical or scientific documents, chat-based customer service, accurate predictions, and personalized recommendations (Haleem et al., 2022). Depending on its version or additional plugins, it can also edit images, audio and other media. Thus, it can be considered a great complementary tool for many strategic activities, including research, process mapping, scenario analysis, industry trend analysis, risk identification and weighting, question generation, and idea creation (Forrest, 2024).

Another commonly used GenAI tool powered by one of the world's leading technology companies, Google, is Google Gemini, which was introduced in December 2023. Unlike ChatGPT, Google Gemini incorporates visual language model technology and does not require additional plugins to process and create outputs from multiple data types, such as audio, images, video and other digital data. This capability enables it to give more complete answers that fit the context, and perform various tasks (Imran & Almusharraf, 2024). Within a strategic management context, its integration with Google applications and its ability to perform complex tasks across multiple domains highlights its flexibility and potential to optimize workflows and enhance productivity (Pande et al., 2024).

Another leading technology company, Microsoft, has also integrated GenAI tools into its applications, with Microsoft Copilot being one of the most well-known examples. Copilot is an AI assistant that can summarize documents, such as Word files, Excel data, and Outlook emails, and generate context-related content based on what is requested to do. This way it helps users complete their daily tasks faster and enhance their productivity in various workplaces (Miranda, 2025). From a business strategy perspective, Copilot can add value to businesses by supporting decision-making processes, and enabling effective data management and predictive analysis, which, in turn, allows executives to make timely and informed decisions (Asundi, 2025).

An alternative GenAI tool that competes with ChatGPT and Gemini is Claude, which was developed by Anthropic in 2023. Claude can handle a wide variety of conversational and text-based tasks, from answering questions and summarizing information to conducting research, writing code, and supporting creative projects, with high levels of predictability and dependability, as it can work with large amounts of text at once (Martins, 2024). Additional example is DALL-E, which creates images from text prompts that can be used in a range of applications, from product design to marketing and advertising (Zhou & Nabus, 2023).

In general, GenAI tools support the integration of AI technologies into various sectors, fostering innovation, collaboration, and creativity, particularly for researchers, business executives, and digital content creators. Additionally, they generate diverse solutions and provide guidance, enabling advancements in education, healthcare, management, finance, scientific research, and other fields (Imran & Almusharraf, 2024).

2.3 Strategic Use Cases of Generative Artificial Intelligence

2.3.1 Marketing and Sales

GenAI reshapes the way businesses implement their marketing and sales strategies, as it allows automation in content creation, personalized communication and real-time prediction of customer preferences. These capabilities increase operational efficiency, reduce costs, and support the development of more dynamic and competitive strategies (Davenport et al., 2019).

First, it personalizes offers and advertisements according to individual consumer preferences. This is critical for customer retention and business growth, as it increases conversion rates and the overall consumer experience (Chaffey & Ellis-Chadwick, 2019). Besides, its ability to analyze the information it finds in social media posts related to purchase preferences and create customer profiles helps businesses to identify trends and adapt their marketing communication in ways that are more persuasive or engaging (Davenport et al., 2019).

Second, it supports automated content creation, so that product descriptions, social media posts and articles can be completed faster, reducing production time and costs and allowing marketing teams to focus on more strategic and creative tasks (Huang & Rust, 2021).

Third, it enhances sales forecasting and price promotion decisions through predictive analytics related to consumer behaviour and market trends, so businesses can develop more targeted sales strategies and increase profitability (Davenport & Ronanki, 2018).

Overall, GenAI's integration in marketing and sales enhances businesses' ability to focus on individual customer preferences, fosters customer engagement, and optimizes sales processes. Its strategic value lies in improving efficiency and strengthening competitiveness in dynamic and volatile market environments (Davenport et al., 2019).

2.3.2 Operations and Supply Chain

GenAI enhances business operations through advanced analytics systems that enable real-time demand forecasting, inventory management, production scheduling and logistics planning, optimizing strategic decision-making and contributing to lower inventory costs and greater customer service levels (Raina et al., 2025). In addition, it enhances predictive maintenance by detecting potential machinery failures in advance and recommending the most effective proactive maintenance actions, reducing downtimes and repair costs while improving system's reliability and overall operational efficiency and continuity (Ucar et al., 2024).

GenAI also supports supply chain management by improving logistical efficiency, allowing businesses to optimize transportation routes, reduce delivery times, minimize wastes and lower operational costs. Moreover, it helps managers to evaluate alternative strategies during periods of supply chain disruptions or crisis situations (Raina et al., 2025). By analyzing data from past collaborations and simulating different scenarios based on current conditions and external risk factors, organizations can anticipate potential failures or delays, strengthening this way supply chain resilience and enabling faster and more effective responses to unexpected disruptions (Ivanov & Dolgui, 2020).

Overall, integrating GenAI into operations and supply chain management facilitates the shift from traditional processes into proactive and agile decision-making systems. Its strategic value lies in increasing efficiency, reducing operational costs, and strengthening business resilience in dynamic business environments (Raina et al., 2025).

2.3.3 Human Resources

GenAI changes the Human Resources (HR) department, as it helps with the recruitment, selection, development and retention of personnel. In this way, it acts as a supportive tool to HR functions and increases the efficiency and transparency of operations (Benabou & Touhami, 2025).

When it comes to recruitment and selection, GenAI is used to automatically analyze resumes, rank people who applied, and find the important skills they need for the job. This saves time for the initial screening of the applicants and makes the whole process faster. GenAI also helps make job descriptions and suggest people for jobs based on how well their skills match, making the process of hiring someone fair and transparent (Benabou & Touhami, 2025).

In development, GenAI analyzes the skills of the employees and creates personalized training programs that help them to learn better and faster. It also helps in evaluating performance, identifying qualified candidates for leadership roles and ensuring continuity in key positions (Benabou & Touhami, 2025).

In retention of the employees, GenAI helps HR department to identify trends, predict when someone might leave, and come up with plans to keep them by making career and training programs that fit what the employee wants and what the company needs. (Benabou & Touhami, 2025).

However, HR is a field that handles large volumes of sensitive employee and candidate data that need strict management according to GDPR regulations. So, even though GenAI is helpful, it cannot replace human judgment completely. When GenAI is used in HR there are concerns about keeping information safe, and its integration requires high levels of data reliability, as algorithms can be biased, thus unfair to applicants or employees. Therefore, when GenAI is used in HR, everything has to be open and honest, and people have to check and ensure that it is being used fairly and in a way that is right (Benabou & Touhami, 2025).

2.3.4 Finance and Risk Management

GenAI changes how companies handle corporate finance through the analysis of quantitative data, economic trends and external factors to figure out what will happen next. This means that companies can analyze things more quickly and accurately, predict what will happen, and manage risks better. So, GenAI is considered a means to assist in strategic decision-making (Huang & Nakamori, 2021).

GenAI is good at finding patterns in data and predicting market trends and profitability potential with higher accuracy than traditional statistical models. This allows companies to make a complete financial forecasting and analysis, and helps them to make informed strategic decisions, especially during periods of financial uncertainty (Guo et al., 2021).

GenAI also helps companies to manage risks and detect fraud, because algorithms can identify unusual transactions in real time, minimizing financial losses in this way (Wamba-Taguimdje et al., 2020).

It then analyzes information about customers, historical records, and economic indicators, and optimizes loan portfolios to support the credit risk assessment and lending decisions (Brynjolfsson & McAfee, 2017).

Overall, GenAI in the financial sector is considered to improve forecasting, assess and reduce risks, and enhance fraud detection. However, its effective adoption requires proper data governance, reliable models, and compliance with regulatory frameworks to ensure its appropriate use and maintain stakeholder trust (Raina et al., 2025).

2.3.5 Research and Development (R&D)

GenAI helps businesses to contact research and development by handling large amounts of data and creating hypothetical scenarios through classification and prediction, that would be difficult or time-consuming to process using traditional methods. Thus, it reduces the time needed for product development and enhances organizations' innovation capacity (Cockburn et al., 2018).

By analyzing market trends and simulating product performance under real conditions, it identifies gaps in the market, combines different technological solutions and proposes new ideas or potential improvements, reducing experimentation costs and improving the quality of final outputs. This allows companies to better adapt products to the market and develop customized products based on individual customer preferences. (Cockburn et al., 2018).

It also facilitates knowledge sharing by creating systems that collect and organize large amounts of data and turn it into useful information. These systems help employees learn continuously and share knowledge more easily, improving collaboration across the organization. This makes GenAI a bridging technology that accelerates knowledge transfer between organizations and enhances the strategic value of networking (Xing et al., 2020).

2.4 Generative Artificial Intelligence and Strategic Management Theories

Strategic management consists of the stages of developing, implementing and evaluating a company's strategy, that is the methods that managers use to satisfy customers' needs, improve operational performance, meet organizational objectives and strengthen the company's market position (Michiotis, 2005).

The use of GenAI as a strategic business tool can be described through established theoretical approaches of strategic management that help in understanding how GenAI can create competitive advantage for businesses, as well as the conditions under which this can be sustainable.

One of the most influential theoretical approaches in strategic management framework is the Resource-Based View (RBV) theory which emphasizes that a company's sustainable competitive advantage depends on the effective use of its unique resources and capabilities that should be valuable, rare, inimitable and non-substitutable (VRIN) (Sanchez-Rodriguez et al., 2025). Under this theory, resources include all assets, competencies, organizational processes and knowledge controlled by the firm and could be tangible, such as buildings, equipment and financial capital, or intangible, such as brand name, patents, reputation and technical knowledge. Capabilities, on the other hand, refer to the firm's unique skills to effectively deploy and coordinate these resources to achieve its strategic objectives (Wartini et al., 2024).

In the context of GenAI, algorithms, LLMs and the ability to apply this technology into business processes can be considered as strategic resources that improve operational efficiency. However, as GenAI tools, such as chatbots and cloud-based services, become widely available, their simple adoption cannot create differentiation. Instead, the RBV theory indicates that GenAI tools can create strategic value and sustainable competitive advantage when integrated into the company's unique organizational resources and processes in ways that are difficult for competitors to imitate (Sanchez-Rodriguez et al., 2025).

A step further goes the Dynamic Capabilities theory, which doesn't focus only on resources, but emphasizes a company's ability to sense opportunities and threats in the external environment, seize them by reallocating resources, and renew or reconfigure those resources to adapt to changing market conditions. Thus, through sensing, seizing and reconfiguring, firms could maintain their competitiveness in rapidly evolving business environments (Sanchez-Rodriguez et al., 2025).

GenAI tools play a vital role in developing dynamic capabilities, as they help businesses to analyze large volumes of data, predict market trends and customer preference changes, redesign processes and business models, and reconfigure organizational resources. In this way, GenAI facilitates strategic decision-making and enables firms to adapt to changes and achieve sustainable competitive advantage in volatile environments (Sanchez-Rodriguez et al., 2025).

Additional commonly known strategic management approaches that relate business strategy to volatile market environments are Porter's Five Forces and PESTEL analysis. Porter's Five Forces framework suggests that strategic success depends on understanding and responding to the competitive environment, and demonstrates that the state of competition in an industry is a composite of five competing forces, as shown below (Michiotis, 2005):

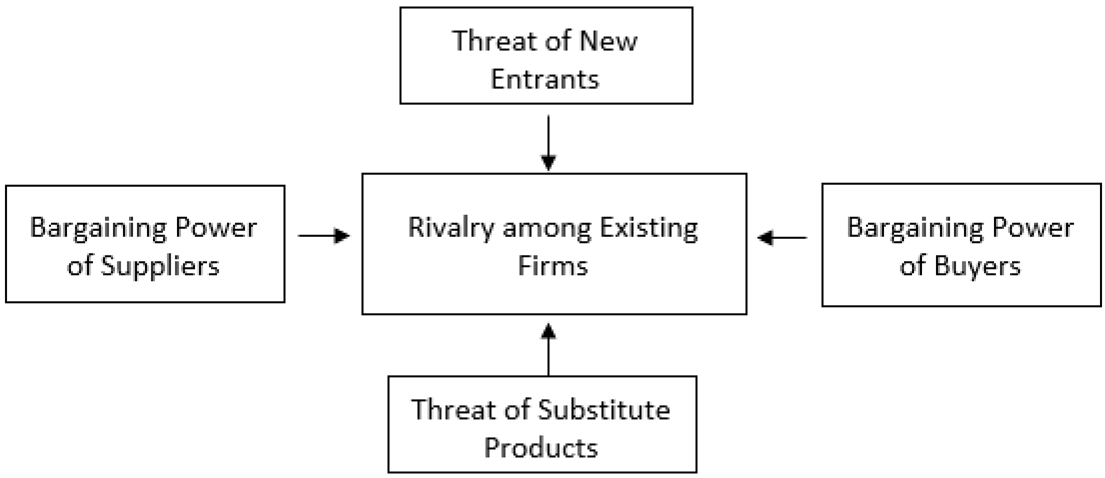

Figure 6 – Porter's Five Forces Model. Source: Michiotis (2005).

Rivalry among existing firms is usually the most powerful of the five competitive forces and depends on the offensive or defensive actions rivals initiate. The threat of new entrants into a market can reduce profitability because they add new production capacity and compete for market share. The bargaining power of buyers can affect prices or product features, when buyers are many or buy high volumes of quantities. Substitute products can reduce profit potential, as they encourage customers to make quality and price comparisons, imposing a ceiling on prices. The bargaining power of suppliers can affect prices and product quality, threatening industry profitability (Michiotis, 2005).

GenAI transforms significantly Porter's Five Forces model by altering competition, market entry barriers, and value chains. Rivalry among existing firms is becoming intensive, as the pressure for innovation and differentiation increases. The threat of new entrants is rising, since GenAI tools reduce the need for technical expertise and lower entry barriers through cloud computing, open-source tools and automation, enabling new firms to enter markets more easily. The bargaining power of buyers is strengthening, as customers can easier access AI applications that allow price and product comparisons, and demand personalized services. Substitute products are growing, as human intervention is limited and traditional business models are replaced by automated customer service and content creation. The bargaining power of suppliers is increasing, as there are still few companies that dominate LLMs that power most GenAI applications (Levin, 2025).

PESTEL analysis evaluates the external forces that affect the environment in which an organization operates and formulates its business strategy, and suggests that those forces can be Political, Economic, Social, Technological, Environmental and Legal. By systematically analyzing these forces, organizations can identify potential risks and opportunities in the macroenvironment, supporting more informed strategic decision-making (Vourdoubas, 2025).

GenAI changes the way that businesses perform PESTEL analysis by automating data collection, processing large volumes of data and delivering real-time insights for each PESTEL factor. Through pattern recognition and predictive analytics, GenAI helps organizations identify trends that foster strategic decision-making and innovation. Natural language processing enables the analysis of textual data from multiple sources, while visual analytics improve communication and understanding of complex external factors. Since PESTEL analysis is often used to identify the external opportunities and threats in a SWOT analysis, GenAI becomes a major strength in strategic management, providing insights that help organizations in formulating effective strategies (Habib, 2024).

3. Methodology

3.1 Research Design

This diploma thesis is a secondary research based on the methodology of Systematic Literature Review (SLR). This method enables the organized, transparent, and reliable collection and analysis of existing scientific research regarding the use of GenAI as a strategic business tool. Unlike a traditional literature review, systematic review follows a regular procedure for searching, selecting, and evaluating available sources. Thus, it reduces bias and increases the reliability of the findings.

The research is primarily qualitative, as it aims to give a critical and deep understanding of the issues highlighted in literature and not statistical results. For this reason, the analysis of the selected studies is based on qualitative thematic analysis. This allows us to categorize the findings into topics related to the research questions of the study, such as: (a) the strategic capabilities of GenAI, (b) its technological limitations, (c) the legal, ethical and operational risks, and (d) the future prospects of its implementation.

The choice of the SLR is the most appropriate for this topic because research on GenAI is fast growing and covers many different fields, including computer science, business administration, strategy, ethics, and law. Besides, GenAI as a technology not only has strong operational applications, but also significant challenges. This requires using a methodology that enables us to gather, compare and interpret findings from different kinds of sources (academic articles, case studies, reports of organizations).

Generally, with the SLR we get a complete and documented perspective of how GenAI can be used as a strategic tool, under what conditions it adds value and creates competitive advantage, and what governance and control mechanisms are necessary for its responsible and effective implementation.

3.2 Bibliography Search Strategy

3.2.1 Databases

The bibliography search process was performed in a systematic and structured way, as the target was to collect reliable and scientifically documented sources related to GenAI and strategic business administration. For this purpose, we chose Google Scholar as the basic database, as it is one of the most used academic search tools worldwide. Its interdisciplinary nature justifies this selection, as the subject of this study relates to technology into business administration. Therefore, it requires access to both technical literature (e.g. machine learning, LLMs, AI systems) and strategic management theories (e.g. competitive advantage, RBV, dynamic capabilities, business innovation).

Google Scholar includes scientific articles from different domains, journals, and research institutions and enables a holistic and cross-disciplinary approach to the topic. It also gives access to academic articles, case studies, research reports and scholarly book chapters that help to understand the practical applications of GenAI in the business sector. As GenAI is rapidly evolving, Google Scholar gives easily access to recent publications, which are important for capturing current trends and developments, and the option to use complex combinations of keywords and filters (such as time limiting posts), which verifies the systematization and transparency of the search. This process ensures that the selection of the sources is not random but based on specific criteria.

3.2.2 Search Keywords & Combinations

The literature search process was based on carefully chosen keywords that highlight GenAI as a technology and its strategic use in business. The keywords were picked to match the research questions of the study. This ensures that the results are directly related to GenAI's capabilities, limitations and future prospects. To make the search more systematic and complete, we used Boolean operators such as AND and OR. These operators help combine terms and adjust the theme of the results. Specifically, we used the OR operator to combine similar or related terms, while we used the AND operator to link different concepts, like technology and strategic management, and to produce more relevant results.

The main search string used is as follows:

("Generative AI" OR "GenAI" OR "Large Language Models")AND("Strategic management" OR "Competitive advantage" OR "RBV")AND("Business" OR "Strategy")

The first group of keywords ("Generative AI" OR "GenAI" OR "Large Language Models") ensures that the results relate to GenAI and LLMs, which are at the core of the technology. The use of different terms is essential because researchers often use different names to describe the same technology.

The second group ("Strategic management" OR "Competitive advantage" OR "RBV") connects technology with strategic management theories and concepts. The inclusion of terms such as "Competitive advantage" and "RBV" extract studies that examine GenAI as a source of strategic value and sustainable competitive advantage.

The third group ("Business" OR "Strategy") narrows the results to the business context, excluding studies of a purely technical nature, unrelated to organizational or strategic applications.

3.2.3 Time Range

The literature search was limited to the years 2015–2025 to ensure that the selected sources were recent and relevant. This period is directly linked to the evolution of AI and, especially, GenAI in business environments.

In the period after 2015 machine learning and deep learning technologies have shown significant progress, as well as neural networks and transformer architectures have been gradually developed. Research into LLMs has accelerated significantly since 2017 with the introduction of transformer models, creating the technological foundations, on which modern GenAI tools were built.

GenAI started to spread fast in the business world after 2022, when advanced language models became available to everyone and companies around the world started to use them. Since then, there has been a jump in research and case studies about how GenAI can be used in important areas like marketing, finance, supply chain, and human resource management

Including studies up to 2025 means that we have the information on how GenAI is being used and what is happening right now. We get to see the trends and the challenges that companies are facing with GenAI. We also get to learn about ways to govern this technology. Meantime, studies published before 2015 were excluded because they mostly refer to traditional forms of AI and not to the genetic dimension that is the focus of this research.

3.3 Inclusion and Exclusion Criteria

To ensure the quality, relevance and reliability of the literature used in the systematic review, clear inclusion and exclusion criteria were established in advance, that enhance the transparency of the methodology and reduce the risk of subjective choice of sources.

3.3.1 Inclusion Criteria

The study mainly included scientific articles that have undergone a peer review process, as this process ensures a high level of scientific validity and reliability of the findings, enhances the theoretical background of research and reduces reliance on undocumented sources. Although in some cases reliable practitioner articles or working papers were used, this was only done when their contribution was directly relevant to the strategic object of the study.

A key inclusion criterion was the direct connection of each study with strategic management or business environment. Specifically, only sources that relate GenAI to strategy formulation, organizational performance, innovation, transformational change, or creating and maintaining a competitive advantage were selected. This criterion is important, as the main goal of the paper is to explore GenAI as a strategic business tool and not as a sole technological innovation.

Also, articles that explicitly refer to either strategic capabilities or risks related to the adoption of GenAI were selected as well. Strategic capabilities include increasing efficiency, accelerating innovation, improving decision-making and developing dynamic capabilities. Respectively, risks include technological limitations, legal and regulatory issues, ethical challenges and organizational dysfunctions. This requirement is directly related to the research questions of the study and ensures that the analysis remains relevant, considering both the opportunities and limitations of the technology in the strategic context.

3.3.2 Exclusion Criteria

Apart from the inclusion criteria, a set of exclusion criteria was applied as well to ensure that the analysis remains coherent and relevant. At first, studies that focused on general technological descriptions, algorithmic improvements, model architectures, mathematical proofs, or programming details, without any mention of the strategic, organizational or business dimension of GenAI, were excluded, since this paper focuses on the business and strategic utilization of this technology, and not on its technical analysis.

Then, duplicated articles identified during the search process were removed. When the same study was revealed, only one version was included in the review. That helped to avoid repetition and overrepresentation of specific authors or findings. This practice is essential in systematic review, as it ensures objectivity and balance of the analysis.

At the end, sources not available in full text were excluded as well, as access to the full content was set as a prerequisite for the proper evaluation of the methodology, results, constraints and the overall contribution of each study. Abstracts alone are not sufficient for systematic analysis, as they may omit critical information necessary for the interpretation and evaluation of the findings.

3.4 Article Selection Process (PRISMA)

The process for the selected articles was based on the principles of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), with the aim of searching and selecting the bibliography in a transparent way. However, as this study is a systematic review and not a complete meta-analysis, the process was limited to a selection of the most relevant and available studies.

The original search was done on the Google Scholar database, using the following search string: ("Generative Artificial Intelligence" OR "GenAI" OR "Large Language Models" OR "LLMs" OR "GPT") AND ("Strategic management" OR "Business strategy" OR "Competitive advantage"). The time horizon was set from 2015 to 2025, and the language was limited to English. Academic articles, working papers, book chapters and practitioner articles with a clear strategic orientation were included. The selection of articles was based on the first results returned by the search engine, sorted by relevance ranking. From the first available results, the titles and summaries were examined and those that met the following criteria were selected:

- a clear link to strategic management
- a reference to competitive advantage or capabilities
- a substantive discussion of impacts, constraints or future directions

In the initial search, 98 articles were identified and screened with no duplicates, as duplicated records were already blocked. 41 out of the 98 articles were excluded, as they were technically oriented and irrelevant to the research questions of the study. 2 articles were not included for technical reasons (the files were not opened) and 5 articles were excluded, as the full text was not available. The final sample consisted of 50 articles, which were available in full text and were considered to be the most relevant to the research questions. These 50 articles formed the basis of the analysis and were categorized based on theoretical framework (e.g. RBV, Dynamic Capabilities View, strategy and governance), strategic focus, reported capabilities, limitations, risks and suggestions for future research. Figure 7 shows the total number of the 50 selected articles that responded to each research question, while the relevant PRISMA Flow Diagram is shown in Figure 8, briefly illustrating the selection process.

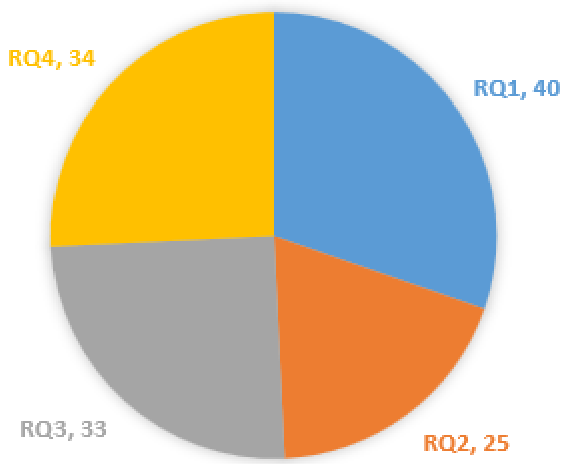

Figure 7 – Distribution of responses across research questions (RQ1–RQ4).
Source: Own elaboration.

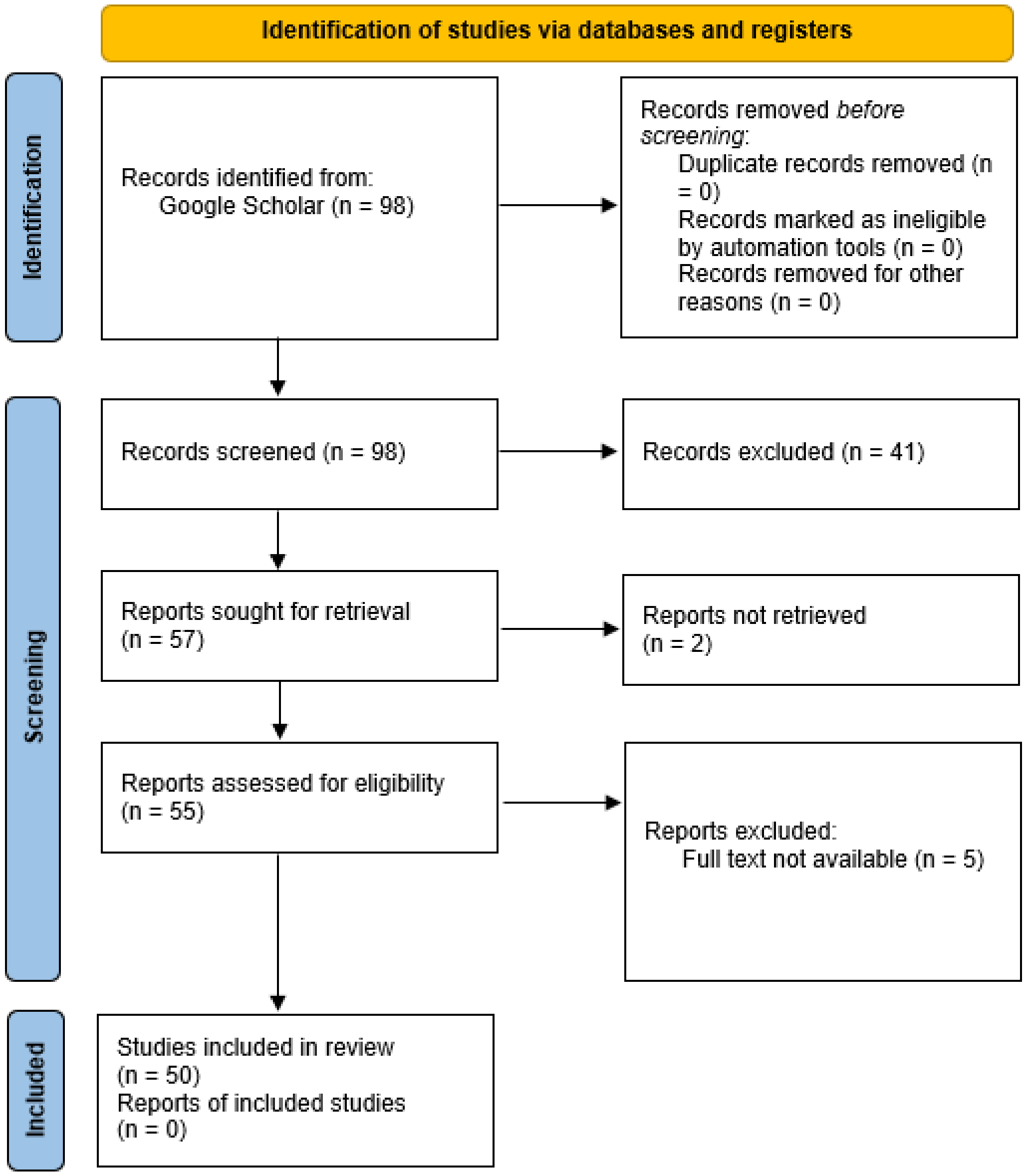

Figure 8 – PRISMA Flow Diagram. Source: Adapted from Page et al, 2021.

3.5 Coding and Analysis Process

To enhance scientific precision, a systematic process of coding and thematic analysis was implemented.

Initially, a data extraction table was created (Table 1), in which the following were recorded for each article:

- Author and year of publication
- Type of study
- Theoretical framework
- Strategic focus
- Reported capabilities
- Reported limitations
- Reported risks
- Proposed future directions

The analysis followed thematic clustering, based on the four research questions (RQ1–RQ4). Each article was classified in terms of its contribution to one or more research fields, as shown in Table 2:

- RQ1: Strategic Capabilities and Transformation
- RQ2: Technological Limitations and Adoption Constraints
- RQ3: Risks for Businesses
- RQ4: Future Perspectives and Strategic Integration

The classification showed that the majority of studies are interdisciplinary in nature, covering more than one research question. This indicates the interconnected nature of the field, where strategic capabilities, limitations, risks, and future prospects are closely interrelated. The analysis was not limited to a descriptive depiction, but proceeded to a comparative and synthetic interpretation, identifying:

- Points of theoretical alignment
- Points of tension or contradiction
- Repeating patterns
- Research gaps

In this way, the study moves from a simple bibliographic review to a conceptual synthesis, leading to the formulation of the proposed strategic framework of Chapter 4.

#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
1	Lanfranchi et al. (2025)	Conceptual / Case Analysis	RBV & Dynamic Capabilities	Competitive advantage (marketing)	Resource reconfiguration	Sectoral limitation	Overdependence, capability gaps	Empirical validation	Resource orchestration
2	Cui et al. (2024)	Conceptual / Managerial	Brand Strategy & RBV	Brand advantage	Differentiation, engagement	Limited empirical data	Brand dilution	Brand-AI strategy research	Practitioner-oriented
3	Lindell (2025)	Conceptual	Strategic Management	Sustainable advantage	Transformation capability	No large-scale validation	Strategic misalignment	Empirical testing	Strategy integration
4	Tuomimaa (2025)	Conceptual / Case	Dynamic Capabilities	Decision-making	Sensing, seizing, transforming	Context specificity	Bias, over-reliance	Longitudinal studies	Strong DCV base
5	Prado & Mantovani (2025)	Empirical	RBV / Value Creation	Value capture	Value capture mechanisms	Industry sample limits	Implementation complexity	Cross-industry research	Value realization
6	Wunder et al. (2025)	Systematic Review	Strategic Management	Use case mapping	Strategic application capability	Early-stage literature	Governance risks	Strategy integration	Mapping study
7	Dzreke (2025)	Conceptual	Competitive Strategy	AI imperative	Strategic positioning	Limited empirical support	Imitation risk	Industry-level studies	Normative
8	Cano-Marin (2024)	Empirical (Text Mining)	Innovation Strategy	Innovation transformation	Innovation enhancement	Data limitations	Tech uncertainty	Data-driven models	Quantitative
9	Ruokonen & Ritala (2025)	Conceptual	Governance & Strategy	Managing GenAI	Orchestration capability	Conceptual focus	Ethical & control risks	Governance frameworks	Managerial control
10	Gutsol (2025)	Conceptual	SCM & DCV	Sustainable suppliers	Data-driven evaluation	Functional limitation	Sustainability bias	AI-SCM models	Supply chain focus
11	Nußbaumer (2025)	Conceptual	RBV	Sources of advantage	Resource recombination	Limited validation	Capability erosion	Firm-level testing	Theoretical depth
12	Halimuzzaman (2025)	Conceptual	Digital Strategy	Strategy transformation	Strategic alignment	Generalized discussion	Disruption risk	Industry studies	Digital emphasis

#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
13	Kanbach et al. (2024)	Conceptual + Cases	Business Model Innovation	BMI via GenAI	Business model reconfiguration	Early evidence	Cannibalization	Longitudinal BMI studies	High rigor
14	Ayyoobi (2025)	Conceptual	Decision Theory	AI in decisions	Analytical capability	Limited depth	Over-automation	Hybrid AI-human models	Innovation link
15	Stores (2025)	Conceptual	Strategic Planning	AI in planning	Planning efficiency	Managerial scope	Implementation barriers	Planning models	Efficiency focus
16	Zavrazhnyi et al. (2024)	Empirical / Hybrid	Digital Transformation	Business transformation	Digital capability	Regional limits	Tech dependency	Cross-country studies	Innovation-driven
17	Bharti et al. (2025)	Conceptual (Book Chapter)	Competitive Strategy & DCV	Competitive frontier	Dynamic capability	Conceptual	Strategic inertia	Capability frameworks	Forward-looking
18	Forsell (2024)	Applied	Marketing Strategy	B2B advantage	Personalization capability	B2B limitation	Privacy risk	AI-sales scaling	Marketing focus
19	Cervini et al. (2023)	Practitioner (HBR Italia)	Strategy & Innovation	Strategy transformation	Experimentation capability	Non-academic	Disruption risk	Adoption practices	Executive lens
20	Cook et al. (2024)	Practitioner (HBR)	Platform Strategy	AI as threat/opportunity	Platform leverage	Advisory	Platform displacement	Repositioning models	Strategic repositioning
21	Marko (2023)	Applied	Digital Strategy	LLM applications	Operational capability	Early maturity	Hallucination risk	Enterprise use cases	Application focus
22	Jean (2025)	Conceptual	Strategic Foresight	AI consulting	Foresight capability	Conceptual validation	Over-reliance	Human-AI models	AI strategist role
23	Brüggemann et al. (2025)	Working Paper	RBV	Expertise & advantage	Implementation capability	Sample limits	Skill gap	Capability-building	Human capital
24	Smith (2025)	Conceptual	Governance & Organization	AI integration	Alignment capability	Early theory stage	Legal/regulatory	Governance research	Institutional
25	Shen & Badulescu (2025)	Empirical	Sustainability & Innovation	Sustainable performance	Sustainable innovation	Sector focus	Compliance risk	AI-regulation nexus	Sustainability
26	Sharma (2023)	Conceptual	Strategic Planning	Forecasting & planning	Scenario modeling	Feasibility limits	Forecast errors	Hybrid forecasting	Automation

#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
27	Björkbom (2024)	Conceptual	Competitive Strategy	SMEs & AI	Strategic agility	SME limitation	Resource constraints	SME adoption models	SME lens
28	Haque (2025)	Conceptual	Digital Ecosystems	Algorithmic enterprise	Data orchestration	Broad scope	Integration risk	Multi-tech models	AI+Blockchain
29	Salmo (2024)	Case Study	Competitive Strategy	Cost savings & value	Efficiency capability	Single case	Implementation dependency	Multi-case research	Consulting case
30	Icons (2025)	Conceptual	Strategy-as-Practice	Strategy work processes	Process enhancement	Limited validation	Cognitive reliance	Process studies	Micro-strategy
31	Mandigo (2024)	Conceptual / Framework Development	Socio-Technical Systems (STS) / Industry 4.0 Integration	GenAI integration framework	Use-case design capability; Integration capability; Socio-technical orchestration	Framework not empirically validated; Broad conceptual scope	Integration complexity; Socio-technical misalignment; Negative societal impacts	Empirical testing in organizations; Validation across industries	Strong implementation/integration framework
32	Ettinger (2025)	Empirical / Qualitative (SLR + Interviews)	Dynamic Capabilities / Enterprise Architecture	Scalable & sustainable GenAI adoption	Enterprise architecture capability; Governance capability; Sensing–seizing–transforming capability	Large-enterprise focus; Qualitative sample limitations; Framework contextuality	Governance gaps; Compliance–innovation tension; Low data governance maturity	Validation across industries; Refinement of EA frameworks for GenAI	Strong governance + scaling perspective
33	Budhwar et al. (2023)	Invited Review / Conceptual	RBV / KBV / Strategic HRM	GenAI implications for HRM strategy	Human capital capability; Talent augmentation; Knowledge management capability	Early-stage conceptual discussion; Limited empirical validation	Bias; Misinformation; Privacy; Ethical dilemmas; Employee displacement / wellbeing risks	HRM-focused empirical research; Human–AI workforce models; Strategic HR adaptation frameworks	Strong people/HR capability perspective
34	AbouElgheit (2025)	Empirical / Qualitative	Disruptive Innovation Theory	Marketing strategic transformation	AI literacy; Strategic thinking; Content	Small-firm / marketing-sector	Over-reliance on AI; Skill gaps;	Research on long-term disruption	Strong disruptive innovatio

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#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
					generation capability; Customer insight capability	focus; Early-stage evidence	Need for human oversight	patterns; Capability development in SMEs	n / SME marketing lens
35	Li (2025)	Conceptual / Comparative Analysis	Strategic Management / Digital Transformation	AI-integrated strategic management	Market forecasting capability; Environmental scanning capability; Strategic agility; Data-driven decision-making	Conceptual design; China-specific context; Limited empirical validation	Data governance issues; Talent gaps; Strategic misalignment; Ethical concerns	Empirical validation across contexts; AI maturity model development	Strong national/contextual strategic transformation lens
36	Rana et al. (2023)	Review/ Systematic Review	Business Innovation / AI Governance	Responsible AI implementation in business	Predictive analytics; Data-driven decision-making; Personalization capability; Process automation capability	Broad review scope; Limited theoretical depth; US-centric context	Workforce displacement; Ethical concerns; Data security; Regulatory gaps	Human-centric AI integration models; Workforce reskilling research; Responsible AI governance frameworks	Broad business innovation and governance overview
37	Impink & Wright (2025)	Empirical / Quantitative	RBV / Competitive Advantage	Startup competitive advantage from GenAI adoption	Early adoption capability; Product development capability; Market timing capability	Startup/high-tech software focus; Funding as proxy for performance	Differentiation erosion; Replicability of AI tools; Competitive crowding; Funding disadvantage	Research on sustainable AI-based differentiation; Customization vs standardization strategies	Strong evidence against automatic GenAI advantage / moat erosion perspective
38	Löfqvist (2025)	Empirical / Qualitative	Value-Based Pricing / Strategic Pricing Theory	Value capture and pricing of B2B GenAI solutions	Value capture capability; Pricing capability; Monetization capability	B2B context focus; Interview-based evidence; Early market stage	Commoditization of GenAI features; Margin erosion; Pricing uncertainty;	Validation of pricing frameworks; Longitudinal studies on GenAI	Strong value capture / commercialization perspective

#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
							Measurement difficulty	monetization	
39	Ratajczak et al. (2023)	Practitioner / Survey Report	Marketing Strategy / Digital Transformation	CMO adoption of GenAI for marketing advantage	Personalization capability; Content generation capability; Insight generation; Market segmentation capability	Practitioner-oriented; Limited academic rigor; Survey-based evidence	Implementation risk; Quality control concerns; Over-reliance on automation	Exploration of new business models; Expanded strategic marketing applications	Executive/CMO perspective on GenAI marketing adoption
40	Avezov (2025)	Quantitative / Comparative Analysis	RBV / Dynamic Capabilities	Economic impact of AI adoption and competitive advantage	Productivity enhancement capability; Sensing–seizing–transforming capability; Data/algorithm infrastructure capability	Reliance on secondary /industry data; Broad multinational scope; Aggregated performance metrics	Regulatory costs; Infrastructure capital intensity; Hype cycle effects	Firm-level longitudinal validation; Deeper causal analysis of AI-performance links	Strong economic/productivity validation of RBV-DCV AI advantage framework
41	Rodriguez et al. (2025)	Empirical / Survey	Technology Acceptance Model (TAM)	GenAI impact on B2B sales performance	Sales process effectiveness; Administrative efficiency; Sales augmentation capability	Single-company healthcare sample; Self-reported data; Limited generalizability	Adoption dependency on managerial support; Technology underutilization risk	Cross-industry validation; Expanded models of GenAI sales adoption	Strong empirical evidence for GenAI-enabled sales performance gains
42	Waters-Lynch et al. (2024)	Conceptual / Working Paper	Dynamic Capabilities / User Innovation / GPT Theory	Managing shadow GenAI use in firms	Organizational sensing capability; Governance capability; Knowledge-sharing capability; Incentive design capability	Conceptual / early-stage theorization; No empirical validation	Shadow innovation opacity; Private employee value capture; Governance blind spots; Lost productivi	Empirical study of	

#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
							ty visibility		
43	Al-Kfairy (2025)	Systematic Literature Review	Digital Transformation / Strategic AI Adoption	Strategic integration of GenAI in organizational settings	Operational efficiency capability; Strategic decision-making capability; Customer engagement capability; Integration capability	Review-based evidence; Limited direct empirical validation; Broad organizational scope	Data privacy concerns; Legacy system integration challenges; Bias in decision-making; Employee resistance/job displacement fears	Research on scale-specific adoption models; Deeper empirical	
44	Sivathanu et al. (2025)	Empirical / Survey	Technology-Organization-Environment (TOE)	GenAI adoption in automotive manufacturing	Absorptive capacity; IT infrastructure capability; Data quality capability; Adoption readiness capability	Automotive/AutoCM context specificity; India-centric manufacturing sample	Hallucination concerns; Adoption barriers in SMEs; Technology readiness constraints	Cross-industry validation; Longitudinal adoption-performance studies	Strong operational/manufacturing adoption determinants perspective
45	Candelon et al. (2023)	Practitioner / Experimental Study	Human–AI Augmentation / Task-Technology Fit	Value creation and destruction from GenAI use	Creative ideation capability; Human-AI augmentation capability; Task allocation capability	Professional-services experimental context; Practitioner study; Task-specific findings	Overtrust outside competence frontier; Reduced diversity of thought; Misapplication risk	Dynamic task-allocation frameworks; Longitudinal studies on frontier-of-competence shifts	Strong task-fit / contingent value perspective on GenAI performance
46	Bohr (2025)	Bibliometric / Topic Modeling Analysis	Dynamic Capabilities	Evolution of AI in business research and capability development	AI adoption capability; Customer service capability; Strategic sensing capability	Research-trend analysis; Indirect evidence on firm capabilities; Abstract-based dataset limitations	Strategic–technical implementation gap; Capability misalignment risk	Research on technical implementation capabilities; Dynamic capability development mechanisms	Meta-level literature mapping of AI business capability evolution

#	Author (Year)	Study Type	Theoretical Lens	Strategic Focus	Capabilities	Limitations Discussed	Risks Discussed	Future Directions	Note
47	Xu et al. (2026)	Theoretical / Modeling	Organizational Theory / Knowledge-Based Hierarchy	GenAI impact on organizational structure and hierarchy design	Workforce design capability; Organizational restructuring capability; Human-AI deployment design capability	Theoretical model only; No empirical validation yet	Skill displacement; Deskilling /upskilling trade-offs; Validation burden due to hallucinations	Empirical testing of deployment architectures; Longitudinal workforce/hierarchy studies	Strong organizational design perspective—deployment mode matters more than adoption intensity
48	Bughin (2024)	Empirical / Quantitative	RBV / Enterprise Capabilities	Firm AI capabilities in GenAI pair coding productivity	Data capability; AI governance capability; Skills upgrade capability; Technical augmentation capability	Working paper; Coding/software engineering context specificity	Quality–productivity trade-off; Poor output quality without complementary capabilities	Broader cross-functional testing of complementary AI capability effects	Strong evidence that GenAI productivity depends on complementary firm AI capabilities
49	Kumar (2023)	Conceptual	Red Queen Effect / Competitive Dynamics	Using GenAI to avoid competitive stagnation and prepare for Industry 5.0	Continuous innovation capability; Customer personalization capability; Strategic renewal capability	Conceptual / normative discussion; Limited empirical support	Imitation trap; Temporary advantage erosion; Competency traps	Empirical testing of GenAI as anti-Red-Queen mechanism; Industry 5.0 strategic models	Competitive dynamics perspective—GenAI as temporary advantage renewal tool
50	Daněk & Pospíšil (2024)	Conceptual / Applied Review	AI-Driven Innovation / Intelligent Agents	Business transformation through GenAI autonomous agents	Autonomous decision-making; Process optimization; Business intelligence capability; Adaptive learning capability	Broad conceptual scope; Limited empirical validation; Cross-sector generalization	Ethical concerns; Over-automation; Autonomous decision risk	Empirical validation of autonomous agent business impact; Governance of AI agents	Emerging autonomous-agent perspective beyond standard GenAI tools

Table 1. Initially recording sources with the PRISMA method

CODING

#	Author (Year)	RQ1	RQ2	RQ3	RQ4
1	Lanfranchi et al. (2025)	✓		✓	✓
2	Cui et al. (2024)	✓	✓	✓	✓
3	Lindell (2025)	✓	✓	✓	✓
4	Tuomimaa (2025)	✓	✓	✓	✓
5	Prado & Mantovani (2025)	✓	✓	✓	✓
6	Wunder et al. (2025)	✓	✓	✓	✓
7	Dzreke (2025)	✓	✓	✓	✓
8	Cano-Marin (2024)	✓	✓	✓	✓
9	Ruokonen & Ritala (2025)	✓		✓	✓
10	Gutsol (2025)	✓	✓	✓	✓
11	Nußbaumer (2025)	✓	✓	✓	
12	Halimuzzaman (2025)	✓	✓	✓	✓
13	Kanbach et al. (2024)	✓	✓	✓	✓
14	Ayyoobi (2025)	✓	✓	✓	✓
15	Stores (2025)	✓	✓	✓	✓
16	Zavrazhnyi et al. (2024)	✓	✓	✓	✓

#	Author (Year)	RQ1	RQ2	RQ3	RQ4
17	Bharti et al. (2025)	✓		✓	✓
18	Forsell (2024)	✓		✓	✓
19	Cervini et al. (2023)	✓		✓	✓
20	Cook et al. (2024)	✓		✓	✓
21	Marko (2023)	✓	✓	✓	✓
22	Jean (2025)	✓	✓	✓	✓
23	Brüggemann et al. (2025)	✓	✓	✓	✓
24	Smith (2025)	✓		✓	✓
25	Shen & Badulescu (2025)	✓	✓	✓	✓
26	Sharma (2023)	✓	✓	✓	✓
27	Björkbom (2024)	✓	✓	✓	✓
28	Haque (2025)	✓	✓	✓	✓
29	Salmo (2024)	✓	✓	✓	✓
30	Icons (2025)	✓	✓	✓	✓
31	Mandigo (2024)				✓
32	Ettinger (2025)			✓	
33	Budhwar et al. (2023)	✓			
34	AbouElgheit (2025)	✓			

#	Author (Year)	RQ1	RQ2	RQ3	RQ4
35	Li (2025)	✓			
36	Rana et al. (2023)			✓	
37	Impink & Wright (2025)	✓			
38	Löfqvist (2025)	✓			
39	Ratajczak et al. (2023)	✓			
40	Avezov (2025)	✓			
41	Rodriguez et al. (2025)	✓			
42	Waters-Lynch et al. (2024)			✓	
43	Al-Kfairy (2025)				✓
44	Sivathanu et al. (2025)		✓		
45	Candelon et al. (2023)		✓		
46	Bohr (2025)				✓
47	Xu et al. (2026)				✓
48	Bughin (2024)	✓			
49	Kumar (2023)	✓			
50	Daněk & Pospíšil (2024)				✓

Table 2. Coding-correlation based on research questions

3.6 Methodology Limitations

Despite the systematic review approach used in the literature search and selection process, some methodological limitations exist, that are important to identify in order to ensure scientific transparency and correct interpretation of the findings.

Initially, there is a risk of bias in publications, since studies with positive or innovative results are usually more likely to be published than the ones with negative or insignificant findings. In the GenAI area, technology is considered transformative and revolutionary. Thus, publications that focus on strategic opportunities and competitive advantage may be overrepresented, while publications that focus on wrong implementations, organizational failures, or unsustainable adoption may be underrepresented. This consequently can create an optimistic overestimation of GenAI's strategic capabilities.

Additionally, the search was limited to sources in English language. While this restriction gives access to the international academic debate, it may exclude important research contributions from non-English speaking countries, as GenAI is strategically adopted and used very differently in various geographies, institutions, and cultures. Thus, studies published in other languages may provide alternative perspectives on issues of regulation, ethics, governance and organizational integration. The linguistic restriction, therefore, may affect the geographical and institutional representativeness of the sample.

Finally, a particularly important limitation relates to the ongoing evolution of GenAI technology. The field is characterized by rapid technological developments, successive versions of models, changes in regulatory mechanisms and continuous adjustment of business practices. Therefore, the conclusions of this study reflect the state of literature and technological maturity at the time that data were collected. Of course, it is possible that some technological weaknesses, such as hallucinations, bias, or interpretability, will be significantly mitigated soon. Although, new risks or strategic challenges might arise. Thus, the dynamic nature of the object means that the results should be considered as temporary rather than definitive or eternal.

4. Analysis of Findings

4.1 Descriptive Results

This chapter shows the descriptive results of the literature review, based on the composition and basic characteristics of the final sample. In total, the sample included 50 articles, all of which were available in full text and considered quite relevant to the research questions of the study, ensuring the methodological consistency and analytical adequacy of the review.

The time range of publications demonstrates a strong concentration during the period 2023–2025 and reflects the rapid academic and professional engagement with GenAI after the popularization of foundation models. Before 2022, few relevant reports were found, while the largest percentage of studies were published in 2024 and 2025. This confirms that the field is still under theoretical and conceptual formation, with limited but still growing empirical evidence.

As long as sectoral breakdown is concerned, a large part of the studies has a general strategic orientation, without focusing exclusively on a specific industrial sector. However, relevant thematic references appear mostly in the domain of marketing, strategic planning and decision-making, digital transformation, business model innovation, and supply chain management. On the contrary, references to financial services, B2B environments and small and medium-sized enterprises (SMEs) appear less frequently. This implies that the debate remains largely at the level of the strategic framework, with selective rather than systematic sectoral analysis.

Regarding the type of studies, most of them are based on theoretical analysis and development of conceptual frameworks or proposals for strategic integration. Few of them are empirical, and include quantitative analyses, case studies or text mining approaches. Additionally, some articles are classified as systematic reviews or practitioner-oriented analyses. This breakdown suggests that the role of GenAI in strategic management is still in a state of theoretical development and empirical evidence is emerging, but still somewhat limited. This finding also explains why emphasis is given on conceptual frameworks and proposed integration models, rather than on actual historical strategic performance data.

4.2 Findings Based on Research Questions

4.2.1 RQ1 – Strategic GenAI Capabilities

As noted in literature, GenAI is more than a tool to automate things. It actually changes the organizational and operational competencies of businesses, acting as a capability amplifier. It makes businesses work better by improving their existing resources, like data, human capital, knowledge of processes and digital setup. Thus, this technology helps businesses learn, analyze and make decisions faster. The importance of GenAI in business strategy however does not come naturally. Instead, it is based on how it is combined with planning, data, skills and rules within a business (Lanfranchi et al., 2025).

GenAI changes the way companies plan and decide and helps them be more flexible and competitive. It actually does this by processing a lot of information that helps companies understand what is happening in the market and how to run their operations smoothly. Thus, it helps them to identify market trends more accurately and make moves to keep up with what people want. It could be said that it is like an assistant that makes big changes happen and helps businesses to adapt to changes and develop more agile, dynamic, and data-driven strategic plans (Li, 2025).

From the RBV Theory perspective, the adoption of GenAI does not automatically create a sustainable competitive advantage, as general-purpose models are widely available and thus easy to imitate. Indeed, startups that integrate GenAI into product development do not necessarily perform better, but in several cases, they get lower funding due to their limited ability to differentiate against competitors, who use the same foundational AI models. This results in homogenization of products and processes and limits the creation of sustainable economic resilience (Impink & Wright, 2025). Differentiation though comes when technology combines unique elements such as proprietary data, specialized expertise, an organizational culture of experimentation, and developed learning routines. In this way, GenAI becomes a resource that meets the VRIO criteria and transforms from a generic technology into a strategic asset. The competitive outcome therefore does not stem from access to technology, but from the unique arrangement of resources and capabilities that accompany it (Lanfranchi et al., 2025).

On operational level, the first and most immediately visible strategic capability concerns the increase in productivity and efficiency. GenAI accelerates the analysis and synthesis of large volumes of information, content production, and support for complex cognitive work, reducing the task completion time and increasing the operational efficiency through better resource utilization and faster decision-making, especially when it is coupled with personalization capabilities, predictive analytics and rapid organizational adaptability. Its value though is not limited to replacing repetitive tasks or human labour but extends to the augmentation of employees by saving time for more complex tasks, and to a possible increase in revenues or market share, under strategic utilization and the businesses' dynamic abilities to detect, capitalize, and transform opportunities (Budhwar et al., 2023, Björkbom, 2024, Zavrazhnyi et al., 2024, Avezov, 2025).

Beyond efficiency, GenAI accelerates innovation and experimentation, as it facilitates ideation, alternative generation, rapid prototyping, and hypothesis testing at lower costs. Moving faster from idea to test and from test to review enhances the organization's dynamic ability to innovate products, services, and business models, and supports strategic transformation. Thus, GenAI doesn't just generate more ideas, but enhances the learning loops tied to dynamic capabilities (Jean, 2025, Cervini et al., 2023).

Particular emphasis is placed on the potential of mass personalization and differentiation through customer experience. Through LLMs, businesses can move beyond imitation-based competition, referred to as the Red Queen Effect, as they can tailor communication and content to different customer segments, develop AI-enabled customized offerings, enhance personalization capabilities, and exploit unstructured customer data for richer market intelligence, maintaining consistent brand identity. GenAI supports sentiment analysis, social listening, and dynamic adaptation of marketing strategies, enhancing engagement and loyalty (Kumar, 2023, Cui et al., 2024, Bharti et al., 2025, Abou Elgheit, 2025). However, the sustainability of this differentiation depends on leveraging proprietary data, that enhance firms' ability to identify customer preferences, rather than horizontal, public models used by everyone (Cook et al., 2024).

On a strategic level, GenAI enhances decision-making, as it supports forecasting, scenario generation and risk analysis, expanding the range of alternatives and improving the quality of management discussion (Ayyoobi, 2025, Wunder et al., 2025). In volatile environments, the ability to produce and compare multiple scenarios enhances organizational resilience and adaptability. Thus, its value here is more related to improving the quality of decisions and reducing cognitive limitations than to simple cost reduction.

The literature emphasizes that GenAI's strategic capabilities are scalable and depend on firms' underlying AI capabilities and the depth of integration. This implies that organizations need to feed GenAI tools with their corporate data to create self-sufficient systems (Cook et al., 2024). Specifically, they need to involve data of high quality, the right technology, people who have AI expertise, and ways to make it all work together (Bughin, 2024). The more they use GenAI with their data and the way they do things the more likely they are to create a system that learns and improves on its own. Meanwhile, new ways of working are coming up, such as being able to ask for what we need, organizing our data, and knowledge structuring. These new ways help us take what we already know and make it something that the whole organization can use (Brüggemann et al., 2025). So, GenAI makes our judgment better by giving us faster access to knowledge and helping us understand it without replacing humans in decision making.

In general studies show that buyers and suppliers think GenAI is mainly valuable for automating tasks and saving time. This means that the main benefit of GenAI for them is that it makes processes more efficient, while it does not necessarily improve the products. They also think that GenAI will become a feature that everyone has access to rather than a special advantage that sets some companies apart. This implies that people think that the value of GenAI will be diminished long-term as more companies start using it, although they are currently willing to pay more for GenAI because it is new and popular. These findings suggest that how valuable people think GenAI is can change, and its value will not matter, unless companies use GenAI along with unique features (Löfqvist, 2025).

Industry evidence further shows that companies mainly see GenAI as a way to boost productivity, efficiency and personalization. They do not think GenAI can create differentiated outputs. According to Boston Consulting Group (BCG, 2023), marketing leaders get benefits from GenAI in areas like content creation and personalization, with productivity gains of up to 30%. However, BCG notes that just using GenAI is not enough. Companies need to implement it in a way that is unique to them, link it with their own data and integrate it into their operations. This means that companies view the basic GenAI capabilities as easy to copy and what really makes GenAI valuable is how it is implemented and to which data it is linked.

Broader enterprise AI literature shows similar findings. There, companies relate GenAI value with terms like increased labor productivity, lower costs, faster time-to-market and better customer value (Avezov, 2025). These findings support the idea that both buyers and suppliers value GenAI according to its performance and not just its capabilities.

4.2.2 RQ2 – Technological Limitations

Despite the strategic capabilities of GenAI, it is confirmed in literature that its adoption and reliability in strategic processes is limited by structural barriers. These barriers stem from the nature of the foundation models, like the probabilistic text production and limited justification, from the quality and availability of data, from the complexity of integration into organizational infrastructures, and from the control and accountability problems when results are used in high-risk decisions. Therefore, the critical question for businesses moves from "what GenAI can do" to "how reliably it can do it" in real-world workflows, where a mistake can cost financially, regulatory, or reputationally (Prado & Mantovani, 2025).

A first limitation comes from technology's disability to satisfy strategic uniqueness when used as a standard solution. The widespread availability of GenAI tools increases cognitive capabilities but at the same time reduces the potential for substantial differentiation, as many organizations use similar models and practices. Under this view, technology functions as a general infrastructure and not as a unique strategic resource. Consequently, the competitive outcome is not about the adoption of the technology, but about how it is integrated, how it is fed with firm-specific data, and how it is organized through processes and governance (Cui et al., 2024).

A second limitation is that generic models often generate generic outputs by nature. Because they are trained in widely available data, they often generate predictable ideas, standardized texts, and strategic proposals that do not reflect the firms' specific knowledge. This makes it less likely that the model will come up with useful strategic insights, and leads to homogenization, particularly when the model is not trained in organizational knowledge or proprietary data. Thus, when multiple organizations use the same model with similar assumptions, the conclusions tend to be similar, something that is particularly discouraging in environments where differentiation is needed (Candelon et al., 2023, Cui et al., 2024).

A third big limitation with GenAI is that it cannot always be up to date. LLMs have limited memory space so they might use outdated information. This causes issues in changing environments where things like new regulations, competitor actions, prices or technology advancements are always being updated. In strategic decisions, even small changes in the environment can overturn results, so static knowledge is a practical problem of reliability. The emergence of solutions like Retrieval-Augmented Generation (RAG) shows that without access to updated and reliable sources, the model can produce convincing but mistaken estimates (Zavrazhnyi et al., 2024).

Another limitation closely related to reliability is the issue of hallucinations that act as a barrier on the practical implementation of GenAI, as models can produce responses that look coherent and professional but are inaccurate or fabricated (Sivathanu et al., 2025). This can lead to wrong strategic decisions, as the risk of misleading confidence increases by the persuasive nature of generated responses that may disregard inaccuracies and create false certainties. This in turn creates a need for systematic oversight and human auditing, reduces the technology's autonomy and, often, limits some of the promised gains in time and cost. However, the literature clearly notes that, without such control mechanisms, organizational trust and therefore adoption dynamics are undermined (Candelon et al., 2023, Zavrazhnyi et al., 2024).

A further key limitation is the dependence on data, as data quality drives the accuracy of the results. Thus, bias, incomplete representativeness, low quality data, or poor data structure can lead to distorted suggestions. On organizational level, this relates to data readiness, as without clean, unified, and well-governed data, GenAI applications remain fragmented and do not scale. In addition, it emerges that the amount of data is not enough as there is a threshold effect where the benefits of additional data are saturated, if there is no algorithmic adaptability and data-decision-action linkage. Otherwise, organizations risk accumulating data without real utilization (Dzreke, 2025).

Another limitation concerns transparency and explainability. The vague nature of models makes it difficult to justify how a conclusion is reached, which constrains strategic use, where executives must be accountable for decisions. Limited explainability fosters mistrust, increases the need for human validation, and is directly linked to the trust issue. In the literature, responsible AI governance appears not only as an ethical choice, but as a technological and organizational prerequisite for the acceptance of GenAI in a strategic environment (Prado & Mantovani, 2025).

The above limitations are intensified by the technical complexity of the strategic use cases. Tasks such as information collection and summary are comparatively easier, while strategy formulation requires creativity, multi-criteria weighting and stakeholder interaction, increasing technical risk. The literature shows that use cases with a higher productivity impact tend to be technically more complex, so the most attractive applications are often the most difficult to implement reliably (Wunder et al., 2025).

A big limitation also is GenAI integration into legacy systems and architectural fragility. GenAI needs to be connected to ERP/CRM, data warehouses, access rules, and monitoring. Embedding difficulty increases implementation costs and time and creates risks of failures, especially in multi-step pipelines where cascading errors can occur. That is why reliability is not treated as an inherent property, but as the result of designing an entire socio-technical system with validation layers and clear protocols (Jean, 2025, Brüggemann et al., 2025).

Finally, literature highlights skills shortage and prompt literacy as a crucial constraint. The issue of lack of skills doesn't imply only that there must be skilled engineers in every organization that adopts GenAI models. It also implies that the final users must be able to evaluate outputs, identify failures, and apply control practices. Thus, even if the technology is available, it may not function properly without human expertise, use instructions, and organizational maturation (Björkbom, 2024).

4.2.3 RQ3 – Legal, Ethical and Operational Risks

GenAI integration into businesses is not just a simple tech upgrade but an addition that affects rules, roles, responsibilities, workflows, and finally the organization's institutional credibility. That is why the risks indicated in the literature go beyond the accuracy of the models and include legal obligations, ethical consequences and operational failures. These risks affect strategic coherence, customer trust and the viability of the competitive position in the market. They are considered as socio-technical phenomena that arise from the interplay of technology, data, people, and institutional frameworks. So, they require multi-layered mitigation policies rather than individual technical solutions (Lanfranchi et al., 2025, Prado & Mantovani, 2025, Tuomimaa, 2025).

On legal level, the biggest risk is the intellectual property protection. The creation of content, like text, images, or code, may cause copyright or trademark violations, or uncertainty about what is considered original and who is the creator. The literature notes that, even when the output seems new, it is not always clarified how it is connected to the training material or created legally, especially when the content is published or commercialized (Lanfranchi et al., 2025). At the same time, there is doubt about who owns the outputs, and specifically who owns the exploitation rights and who and under what conditions can reuse the content, especially when third-party providers, external models or co-creation processes are involved (Rana et al., 2023, Bharti et al., 2025).

Apart from that, there is also the risk of accountability. When a GenAI system shapes supplier choices, communication campaigns, product features, or compliance decisions, an incorrect output creates conflict of responsibility among the end user, the team that integrated the system, the administration that approved the use, and the model provider. This uncertainty damages the organizational coherence and creates the need for internal controls, clear oversight roles, publication approval procedures and auditing (Lanfranchi et al., 2025, Jean, 2025).

Privacy and personal data protection are another legal risks, particularly with applications for service automation, personalized offers, and social listening. The literature refers to the personalization-privacy paradox, according to which the higher the personalization of services, the more data needed to be collected and analyzed. This creates greater risks of privacy violations or personal data use that exceed the customer's permissions. Risk is even greater in multimodal and perceptual AI applications, where data is richer and possibly easier to identify. Thus, companies find themselves dealing not only with legal risks, like sanctions or restrictions, but also the potential damage to their reputation, since privacy is closely tied to the level of trust they build with their customers (Rana et al., 2023, Prado & Mantovani, 2025).

On ethical level, bias in algorithms is particularly important, either it is caused by bias in the training data or by the way organizations use the system. It can cause false assessments of the market conditions, improper customer targeting, or unfair treatment in HR and customer service, with reputational and legitimacy costs for the businesses (Prado & Mantovani, 2025). Likewise, hallucinations can give wrong information to customers, as they are often presented as persuasive matter of facts, while they never happened . Here the ethical dimension is not only about reflecting the truth, but about the responsibility of the organization when producing content that can influence others' decisions (Rana et al., 2023, Zavrazhnyi et al., 2024).

Another ethical issue arises when companies use GenAI to declare who they are as brands and how they speak to their customers, that is when they use GenAI to build their brand identity. The unstructured use of GenAI in marketing and communication can alter companies' brand authenticity and lead to inconsistent styles as conversation grows, discouraging their expanding strategies and harming their reputation. Under these conditions, GenAI is considered as an impressive tool that has no clear strategy, and, without human oversight, results in producing content quantity but eroding trust or differentiation capabilities (Cui et al., 2024).

An additional ethical risk refers to security and malicious use of GenAI, as it increases phishing and social engineering, especially in corporate environments, where it can be exploited to extract unauthorized sensitive data. A cyberattack, as it is called, is not just a simple technical incident but a significant threat to organizational credibility and customers' sense of security (Bharti et al., 2025, Cook et al., 2024).

Beyond the legal and ethical ones, GenAI integration comes with operational risks as well, that often determine whether an initiative will survive after the experimentation stage. When organizations do not employ AI expertise or they do not have clear instructions for its use, then GenAI creates uncertainty, resistance to change, and fear of losing control. Operational failure comes, not from the application of insufficient GenAI model, but from the ambiguity of goals, technical immaturity of the organization, weakness to evaluate outputs and absence of validation processes. This, in turn, results in decisions that are based on insufficiently verified information (Rana et al., 2023, Tuomimaa, 2025).

Related is the phenomenon of *shadow user innovation,* when employees experiment and use GenAI tools autonomously, without clear approval, guidance or supervision from management. This opacity creates serious governance blind spots, as the business often does not know exactly where the technology is used, with what data, for what decisions and with what level of control over the outputs produced. As a result, accountability, quality control, compliance, and sensitive information protection risks arise from this interplay of tools, incentives, routines, policies, and governance structures, while the productive use of GenAI remains fragmented and difficult to convert into visible operational capability

(Waters-Lynch et al., 2024). Therefore, the risk of false confidence is created, as people trust the persuasiveness and speed of the output instead of its validity (Cervini et al., 2023).

At the same time, the risk of deskilling and capability erosion is highlighted. Over-delegating creative or strategic functions to GenAI can gradually weaken internal capabilities, diminishing teams' ability to spot mistakes, generate authentic thinking, or innovate without the tool. In the long run, this creates dependence not only on technology but also on suppliers, versions and access policies, increasing the strategic risk of changes in the market or regulatory frameworks (Lanfranchi et al., 2025).

When GenAI is used in more complex ways, operational risks include instability and consequent errors, as small errors can lead to decisions, thus greater errors, that impact service levels and business continuity. This increases the need for quality control, validation processes and clear operating rules, because otherwise the risk is not just a wrong answer from the tool, but a repeated malfunction that affects real functions (Brüggemann et al., 2025, Dhar, 2025).

Overall, as noted in the literature, the majority of GenAI's legal, ethical, and operational risks comes from weak governance controls and incomplete integration strategies into organizations. Lack in AI expertise, that could solve the problem of data governance, and the need for balance between compliance and innovation are key factors that hinder secure and effective scaling of GenAI adoption. This finding implies that GenAI risks are not just technological in nature, but challenges that could be faced through clear oversight structures, accountability architectures, and organizational mechanisms that balance innovation and regulatory compliance (Ettinger, 2025).

4.2.4 RQ4 – Future Prospects

The future of GenAI is not just about models enriching or applications increasing but depends on its strategic integration across businesses. Since GenAI use is becoming more and more popular, it is up to how companies will link this technology to idiosyncratic data, organizational insights, learning mechanisms, and control structures that are difficult to imitate, so they gain competitive advantage (Lanfranchi et al., 2025, Cui et al., 2024). Thus, the future prospect is not just about more automation but about how a generic technology can be used to create competitiveness and sustainability.

Under the RBV and Dynamic Capabilities theories, GenAI is not a source of advantage unless it is utilized in ways that add value to businesses. This can only be done when GenAI is linked and fed with companies' proprietary data, routines, culture and know-how in ways that are inimitable for competitors, and provided that it is constantly updated, as a dynamic capability (Lanfranchi et al., 2025).

As a baseline, using generic tools creates limited differentiation, because everyone uses the same models. On the contrary, when organizations enrich these tools with their own data and institutional knowledge, the benefits become much greater. The most advanced stage is collaborative logic, where GenAI not only generates outputs but also improves through feedback, and is based on deeper interaction with humans. As a next strategic frontier, the shift towards multimodal experiences is proposed, where differentiation shifts from content production to the creation of experiences and relationships that are more difficult to replicate (Cui et al., 2024).

However, this transition is not automatic, as GenAI does not create advantage without administrative skills that activate sensing, seizing, and transforming, that is the ability to identify the right use cases, leverage them at the right time, and transform them into organizational routines. This requires clear AI strategy and guidelines, a culture of readiness, training, and investments in solutions or partnerships that address capability gaps. In other words, the future of GenAI depends less on the intelligence of the model and more on the maturity of management in integrating it effectively (Tuomimaa, 2025). This implies that GenAI may either upskill or deskill the workforce depending on whether it is deployed for automation or augmentation, while organizational hierarchies are likely to evolve non-linearly rather than flatten immediately. Importantly, demand for senior expertise may increase in the medium term due to the continued need for validation, oversight, and exception handling. These findings indicate that future workforce transformation under GenAI will depend on strategic implementation choices rather than technological capability alone (Xu et al., 2026).

The emphasis on the future strategic integration of GenAI is also addressed by the socio-technical perspective, under which the value of technology does not only depend on the existence of individual use cases, but on how they are systematically designed and integrated into the organization. In particular, it is suggested that organizations should develop GenAI use cases at baseline, intermediate, and meta-level, and consider their integration with vertical, horizontal, and end-to-end logic so that the technology can be connected to the organization's operations, workflows, and broader socio-technical structures. In this way, the future prospects of GenAI are not only linked to the technical refinement of models, but to the development of strategic planning and organizational orchestration frameworks that allow for scalable and coherent integration (Mandigo, 2024).

Another future concern is how organizations consider strategic performance, as they usually separate value creation from value capture. While value creation, which includes faster analysis, higher productivity, and new customer experiences, is numerically measured through companies' KPIs, value capture remains limited, especially when the value is intangible, like brand name, know-how and reputation. The literature then notes that the challenge is how organizations measure the impact of GenAI adoption on areas such as brand value, organizational learning, and legitimacy. This implies that success will depend on their ability to make GenAI part of daily routine operations, show tangible benefits, and gain stakeholder trust in its value (Prado & Mantovani, 2025).

When it comes to the practical implementation of GenAI, organizations need to combine simple technical tools that help them identify gaps in data and validation processes with more complex versions that link to their proprietary data and culture in ways that are difficult to replicate. In other words, integration should be done gradually as a maturation process through task decomposition, data requirements, prototypes, and measurements, and not as a rapid digital initiative (Wunder et al., 2025). Under these conditions, GenAI will increasingly expand and become incorporated into a wide range of organizational functions, including marketing, finance, business intelligence, HR and operations.

The future of GenAI is going to be really exciting with the creation of more autonomous AI agents that will be able to work in real time, adjust to the current conditions and make decisions without needing too much help from people. The use of GenAI is also becoming more popular in learning, where it enables personalized training and assessment, so people learn in a way that is tailored to them. This makes learning fun and interesting, while companies can use GenAI to help their employees evolve professionally. There are some things though that impact the future benefits that arise from the effective use of GenAI, and companies need to think about. They need to make sure they treat people fairly and keep their information private. They also need to think about how much it will cost to implement GenAI and how they will help their employees learn skills (Daněk & Pospíšil, 2024).

Looking to the future, the literature notes that GenAI is a part of how companies work and of their digital transformation. It is used in ways that help people make decisions and make different parts of the company work together. To make this change happen, companies need to come up with ways to govern GenAI . This means that companies need to make rules, have people watch over GenAI to make sure it is fair, and have frameworks to make sure GenAI is used correctly. At the time companies need to help their workers learn new skills and understand GenAI. The important thing is that, for GenAI to be used in the long term, people need to work together with GenAI in a way that combines what people are good at with what GenAI is good at. This way, GenAI will help people make decisions and do their jobs more easily rather than replace them (Al-Kfairy, 2025).

Overall, the literature suggests that the big future challenge is the gap between trying something and actually making it work everywhere. Lots of companies start projects but not many can make these projects work for the whole company. To fix this problem, companies need to change the way they work and invest in skills. They also need to make sure they are using GenAI responsibly, because trust is very important if we want to make things work on a scale. So the future of GenAI in strategic management is shaping up to be a transition from a productivity tool to an organizational operating system that combines technology, data, people, and rules, and that is exactly what will determine who will reap sustainable value (Lanfranchi et al., 2025).

4.3 Synthetic Analysis

The findings of the four research questions show that GenAI is not another digital tool, but a technology that can change the way businesses work, learn, make decisions and create value. However, just using GenAI does not make it important, but its strategic value depends on how it fits into the rest of the business systems like resources, processes, data and governance.

First, GenAI helps businesses learn faster, make better decisions and be more productive and flexible. At the same time, it helps businesses come up with new ideas, try them out and make them real, and satisfy their customers by giving them what they want. However, the strategic value of GenAI depends on whether it is connected with complementary organizational resources, such as proprietary data, experience with AI, good governance, and a culture that likes to learn and try new things. The main point that everyone agrees on is that GenAI is rarely a VRIO resource on its own, but it becomes a good strategy when it is used with resources that are hard to copy (Lanfranchi et al., 2025).

Second, GenAI has some technological barriers that affect how well it works. These barriers include things like hallucinations, limited explainability about what it does, dependence on data quality, making similar outputs and being hard to connect to existing systems. These issues mean that GenAI cannot fully automate high-risk tasks on its own and require human supervision. The real question then is not if GenAI can do a task but if it can do it reliably with people accountable and consistently so it can be used in critical tasks, where mistakes can have consequences.

Third, the fact that GenAI is widely used creates a lot of legal, ethical, and operational risks, which are not about the technology itself but about how we use it. Issues about who owns the results, personal data protection, accountability, algorithmic bias, spread of false information, security threats and organizational deskilling are typical examples of these issues that can limit the sustainable use of technology. Similarly to this view, the literature notes that most of these risks are not just because of GenAI itself, but because there are insufficient rules and plans for how to properly use it. So, the successful use of GenAI presupposes that we have to think about it as a big challenge for the whole organization and not just as a simple tool that we use.

Fourth, when we think about what the future of GenAI might be, we can see that it is changing from a tool that helps us be more productive to a fundamental part of how businesses work. The literature states that what will make businesses different from each other in the future is not just that they use GenAI, but how well they can make it a part of everything they do. GenAI will be used in different ways, and it will work closely with people to help them make decisions, learn new things, and do their daily work. GenAI will not replace people, but it will help them do their jobs better. So, organizational competitiveness in the future will depend on whether businesses make GenAI a strong part of who they are and not just something they use sometimes. They have to make GenAI a part of their organization that is always changing and getting better.

The analysis of the findings, which are shown in Table 3, shows that GenAI should be seen as a tool that helps businesses change and improve over time than a solution that can be used on its own. This is because GenAI has a lot of potential to help companies become more efficient, learn new things, come up with new ideas, and make good decisions quickly. However, the real value of GenAI depends on how it is integrated into the company as a whole. The sustainable utilization of GenAI depends on companies' ability to change the way they use technology so that it is not a tool that they use but a part of how they do business. This means that companies need to connect their GenAI systems with important parts of their business such as the data they use, the way they are organized, the people who work for them, and the way they are structured.

Consequently, the main conclusion of this research is that GenAI is not something that can give a company a lasting advantage over others on its own. Instead, GenAI is something that can help a company make the most of its strengths, and its value depends on how, where and under what conditions it is used. Companies that can combine GenAI with diversified resources, such as good leadership, strong governance structures and the ability to adapt to change, are more likely to transform GenAI from an operational improvement tool to a sustainable strategic lever of competitiveness. Businesses that have these things in place can use GenAI to make their operations better, and to help them make decisions and achieve their goals, which can lead to long term success.

Thematic axis	Points of convergence	Points of tension / contradiction	Conditions for the creation of Competitive Advantage	When an advantage is NOT created
Strategic role of GenAI	GenAI primarily functions as a capability amplifier rather than a standalone strategic resource	Democratization vs. Differentiation	When integrated into idiosyncratic resources, such as proprietary data, organizational routines, governance, and learning culture	When used as a generic tool with no customization and no connection to firm-specific capabilities
Productivity & performance	The first benefits appear mainly in productivity, efficiency and time savings	Value creation vs. Value capture	When productivity gains translate into process redesign, better resource allocation and faster strategic execution	When the use remains at a fragmented, individual or ad hoc level without organizational utilization
Innovation & learning	GenAI accelerates ideation,	More ideas vs. Better ideas	When technology is linked to	When it produces only generic outputs

Thematic axis	Points of convergence	Points of tension / contradiction	Conditions for the creation of Competitive Advantage	When an advantage is NOT created
	experimentation, prototyping, and learning loops		feedback loops, organizational learning and product/service renewal mechanisms	or increases the quantity without qualitative utilization
Strategic decision-making	Supports forecasting, scenario generation, information synthesis and risk analysis	Faster decisions vs. Better decisions	When used as judgment augmentation with human oversight, quality data and clear managerial use cases	When used uncritically in high-risk decisions without verification and explainability
Competitive differentiation	Technology alone rarely makes a difference, as it is widely accessible	Standardization vs. Uniqueness	When combined with difficulty imitating assets and leads to unique experiences, services or decision routines	When multiple competitors use the same public models in similar ways
Data & technology infrastructure	GenAI's value depends crucially on data quality, integration, and	More data vs. Better data	When there is clean, up-to-date, structured data and an	When data fragmentation, poor governance or inability to

Thematic axis	Points of convergence	Points of tension / contradiction	Conditions for the creation of Competitive Advantage	When an advantage is NOT created
	infrastructure readiness		architecture that supports reliable use of	connect the model to enterprise systems prevails
Technological limitations	Hallucinations, explainability gaps, output homogenization, and capability limits are key barriers	High potential vs. Low reliability	When constraints are converted into manageable parameters through validation layers, RAG, monitoring, and human-in-the-loop	When the technology is considered reliable "by default" and integrated without controls
Legal & ethical risks	Copyright, privacy, bias, accountability and transparency emerge as constant risks	Innovation speed vs. Regulatory/ethical compliance	When there are clear governance frameworks, ethical safeguards, roles of responsibility and usage policies	When the use is uncontrolled, without oversight, accountability or compliance mechanisms
Organizational integration	GenAI's value hinges on the depth of	Pilot success vs. Enterprise scale	When the business moves from isolated	When GenAI Remains an Experimentation

Thematic axis	Points of convergence	Points of tension / contradiction	Conditions for the creation of Competitive Advantage	When an advantage is NOT created
	integration into workflows and routines		pilots to cross-functional, embedded capability with change management and AI literacy	Tool Without Scaling, Ownership, and Procedural Integration
Human capital & skills	GenAI does not abolish the role of humans, but changes its content	Automation vs. Augmentation	When employees are upgraded to roles of judgment, control, composition and strategic supervision	When deskilling, overreliance or shadow use is created without training and guidance
Future prospects	The future shows a transition from productivity tool to embedded organizational capability	Enterprise transformation vs. Commodity tool	When GenAI is institutionalized as part of the operating model, learning systems, and strategic architecture	When it is treated only as a temporary efficiency tool or hype-driven solution

Table 3. Summary of findings

4.4 Proposed Conceptual Framework

The findings on research questions of chapter 4.2 and the synthetic analysis of chapter 4.3, propose a comprehensive strategic framework that shows how GenAI can be changed from a tool to a source of sustainable competitive advantage. This framework is organized around a sequential and dynamic chain of relationships, as shown in Figure 9:

Inputs → Capabilities → Strategic Outcomes → Risks → Governance Controls → Sustainable Advantage

The logic of the model is not linear and static, but circular and evolutionary. Outcomes and governance mechanisms re-influence inputs through feedback loops and organizational learning, strengthening or weakening the organization's strategic position over time.

4.4.1 Inputs: Strategic Conditions and Resources

The first level of the framework refers to the strategic resources and conditions that GenAI needs in order to work effectively. As it is noted in the literature, just using GenAI or tools that offer GenAI services, does not create a strategic advantage itself. The value of GenAI depends on what kind of resources are used with it and how these resources are organized. One important thing is that companies have their own proprietary data assets, with which they can enrich models and make them domain specific. Also, companies need to have digital infrastructure, that is ways to move data around special computer systems and cloud storage, so GenAI can be used safely and reliably. At the same time, companies need to have staff who understand GenAI and can use it well, which means that they can ask GenAI the right questions, understand what GenAI says, and know what GenAI can and cannot do. Finally, companies need to have a culture of learning and a clear plan for what they want to achieve with GenAI, otherwise it remains just a tool that it is not used to its full potential.

4.4.2 Capabilities: Transforming Resources into Dynamic Capabilities

The second level is about taking information and turning it into skills that the organization can use. GenAI doesn't add value just because it is there, but because it is used in daily tasks and changes the way that organizations work. At this point, technology changes the way things are done and helps in making the organizations better at what they do.

Some important skills that are developed include making things more efficient, being proactive about plans and what might happen, coming up with ideas quickly, creating new designs, and improving customer experience. It is also very important to develop skills that can change quickly, like being able to learn and adapt to new situations. At this level, GenAI changes from a tool to a normal part of how the organization makes decisions and creates value.

4.4.3 Strategic Outcomes: Turning Capabilities into Strategic Outcomes

The above skills really produce strategic results when companies make a difference in the market. When companies use these skills, they can do things like increase productivity, cut costs, make decisions faster, get things to market quicker, and make their products special for each customer. GenAI can also help companies to develop new business models and new ways for capturing value. However, just because companies can make something valuable, it does not mean that they can keep that value. Instead, they need to have a plan, make sure that everything is aligned with the business model, and be ready to adapt to changes in order to really get ahead of the competition. Otherwise, they will only see benefits that do not create a sustainable advantage.

4.4.4 Risks: Technological, Legal and Operational Risks

The fourth level of the framework is about the potential risks that follow the strategic utilization of GenAI. Technological limitations, such as hallucinations, bias in the data, gaps in understanding how GenAI works, and issues with the quality of the data it uses, can create doubts about the decisions made by GenAI. At the same time, there are legal and ethical issues to think about, like who owns the outputs, how private the information is, who is responsible, and if the rules are followed. These issues can cause reputational or financial costs for the companies. Also, there are operational risks like relying much on the system, losing or undermining staff's skills, and finding complexities in working with old technology systems. These risks are not external features of the model, but part of how GenAI works.

4.4.5 Governance Controls: Management and Control Mechanisms

To avoid turning risks into strategic costs, the framework suggests governance control as a critical mechanism. This governance control includes usage policies, human oversight, validation mechanisms, data governance frameworks, ethical-by-design architecture, and quality control processes. Clear roles, approval procedures, audit trails and compliance mechanisms help as well, as they build trust within an organization. This trust helps organizations accept and use GenAI easily and is crucial for growth and expansion. Without robust governance, even the most advanced technological applications remain limited or create unforeseen costs.

4.4.6 Sustainable Advantage: The Dynamic Balance

The final stage of the framework concerns sustainable competitive advantage. GenAI leads to sustainable advantage only when:

1. It is combined with rare and hard-to-copy resources.
2. It is deeply integrated into organizational routines.
3. It is supported by continuous learning and adaptation mechanisms.
4. It is framed by strong governance and institutional legitimacy.

The advantage is not static, but the result of a dynamic balance between innovation and control, speed and reliability, automation and human judgment. If governance controls and learning mechanisms work effectively, then strategic outcomes reinforce inputs through accumulation of data, experience, and organizational knowledge, creating a self-reinforcing cycle.

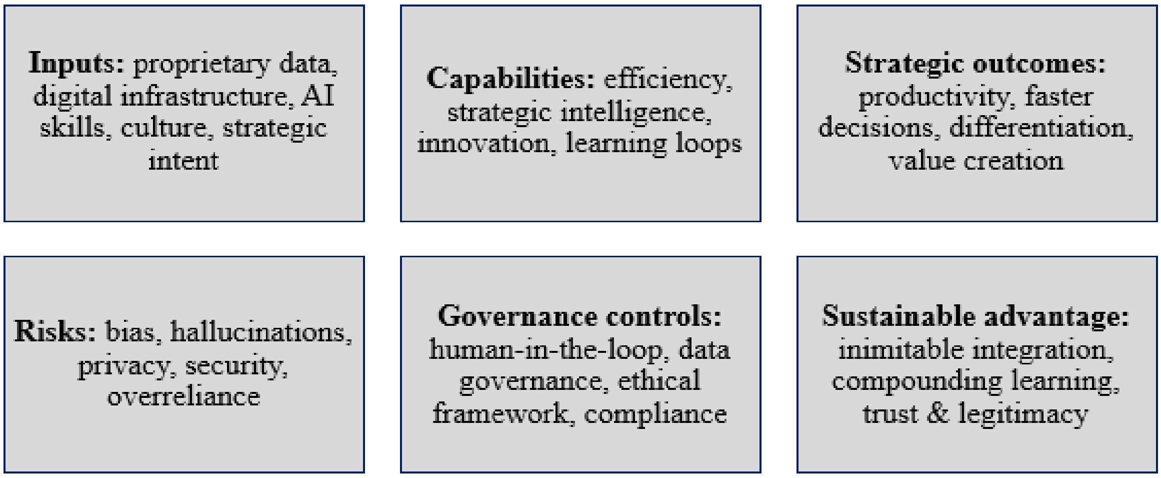

Figure 9: Conceptual Framework for the Strategic Integration of Generative AI. Source: Own elaboration.

5. Conclusions and Strategic Recommendations

5.1 Answers to Research Questions

RQ1: What are the strategic capabilities of GenAI for businesses?

The literature suggests that GenAI primarily functions as a dynamic capability tool rather than a single strategic resource that enhances data use, human capital, and decision-making processes. It affects the opportunities detection (sensing), resource utilization (seizing) and organizational transformation (transforming), enhancing cognitive processing, speed of analysis and the creation of alternative strategic options, and boosting productivity, innovation, and customer personalization. However, its strategic value does not arise from the technology itself, but from the degree to which it is integrated into idiosyncratic resources, such as proprietary data, expertise, and organizational routines. Therefore, GenAI transforms strategic capabilities when it works in addition to existing assets rather than as a fragmented tool.

RQ2: What technological limitations impact the reliability and adoption of GenAI in strategic processes?

The research highlights that GenAI's reliability is influenced by structural technological limitations, such as hallucinations, reliance on data quality, algorithmic bias, and limited transparency and explainability. The fact that GenAI is widely used means that businesses get similar outputs, thus it is difficult for them to stand out and create strategic differentiation. Meanwhile, integration issues in legacy systems, lack of specialized skills and high structural complexity create gaps, when it comes from experimentation to practice. GenAI, therefore, is not a standard solution for strategic use but requires operational infrastructures, human oversight and validation, and organizational readiness to become reliable and acceptable in critical decision-making processes.

RQ3: What risks arise from integrating GenAI into businesses and how they can be addressed?

The use of GenAI in businesses comes with a lot of problems that are not just about technology but about the law, what is morally right and wrong, and how businesses operate. When we talk about the law, we have to consider who owns the outputs that GenAI creates, and how we can hold people accountable when GenAI does something wrong. We also have to think about data privacy because GenAI uses a lot of data and this can lead to problems like violating the GDPR rules. Ethically, risks such as bias, misinformation, and loss of trust emerge, as GenAI can produce misleading or discriminatory outputs that affect brand authenticity. When it comes to running a business, there are also risks with using GenAI. If we rely much on it, our employees might not learn all the skills they need. It can also be hard to get GenAI to work with obsolete systems. These problems can lead to false decisions, reduced human capabilities, and technical failures. This is especially true when there is a lack of skills, processes, and organizational readiness in place. To deal with these problems we need to have a plan for how to use GenAI. This plan should include rules for using GenAI, and people should be in charge of making sure it is used correctly. We also need to make sure we are protecting personal data and that we are using GenAI in a fair and right way. Additionally, businesses need to teach their employees how to use GenAI and change the way they do things so that GenAI is used in the same way by everyone. This ensures that GenAI enables trust and long-term competitive advantage.

RQ4: What are the future prospects for effective strategic integration of GenAI?

The future of GenAI is going to be really important. GenAI will probably change to include different types of systems that work together like foundation models and databases. This means that GenAI will be able to learn and adapt without needing to be retrained all the time. To make this work, companies will need to have management and rules for using GenAI. The future of its strategic utilization will not be determined by access to technology, but by the ability of businesses to orchestrate it within dynamic ecosystems, manage risks, and maintain a balance between innovation and control.

5.2 Theoretical Contribution

The current study helps to better understand strategic management by adding GenAI into existing theoretical frameworks and showing how technology changes important strategic ideas. This mainly extends to the RBV Theory, the theory of Dynamic Capabilities and Porter's Five Forces approach to competition.

Under the RBV Theory, the study notes that GenAI is not a resource that meets the VRIO (valuable, rare, inimitable, organized) criteria because many people can access it. However, GenAI makes other resources more valuable, particularly proprietary data, organizational knowledge, and internal routines. In this way, RBV is enriched, as the strategic value shifts from possessing the technology to the ability to orchestrate and combine it with temperamental resources. This means the focus is on using GenAI with resources and not just having it.

In terms of the theory of Dynamic Capabilities, the research shows that GenAI helps companies to sense, seize and transform opportunities faster. It does this by analyzing data quickly to find chances, by suggesting scenarios that lead to optimal decision-making, and by changing how things are done through automation and process reengineering. However, for GenAI to really help, companies need to be ready and have learning and governance systems. Thus, GenAI does not replace dynamic capabilities but makes them work better and faster.

Finally, the study offers a modern reading of Porter's Five Forces approach. On the one hand, GenAI changes the structure of the industry by reducing barriers to entry and making it easier for new companies to enter into the market. On the other hand, it gives companies new ways to differentiate through personalized products and services, customer experience improvement, and business model innovation. GenAI also changes the nature of the supply chain, as it affects areas like marketing, operations, R&D, and customer service, all at the same time. So, GenAI does not decline Porter's logic of competition, but redefines it, shifting the focus from just being in a good position to being able to adapt and use new technology all the time.

5.3 Practical Strategic Suggestions

5.3.1 Governance Framework

The strategic use of GenAI needs a clear governance plan about how it is used in an organization. First, a formal AI policy is needed, which states what GenAI can be used for, who can use it, and what they can and cannot do. This policy should include principles of transparency, accountability and ethical use, as well as clear guidelines on how to handle sensitive information. Second, a thorough risk assessment process is required before using GenAI for tasks. This assessment should consider technological risks like hallucinations and bias, legal risks like intellectual property and compliance issues, and operational risks like system dependency and integration failures. Risk assessment should not be done after implementation but integrated in advance into the design. Third, human oversight is necessary for GenAI to be credible. It should not function as a standalone tool in critical strategic decisions. This means that people with institutional responsibility validate, interpret and make decisions based on GenAI outputs.

5.3.2 Data Strategy

The effectiveness of GenAI directly depends on the quality and architecture of the data. This means that organizations need to develop an integrated data strategy. Firstly, ensuring the quality of the data quality is very important. Data must be accurate, updated, structured and free from systematic distortions. Organizations should invest in cleaning the data, making it standard, and managing the metadata. This is a priority and not just a technical thing to do. Secondly, the data needs to be stored and strongly protected either by using encryption or by controlling who can access the data. There should also be rules for sharing the data in order to reduce the risk of it being leaked or used badly. Especially in regulated industries, following these rules is essential to maintain trust. Third, using RAG (Retrieval-Augmented Generation) architecture makes the results more reliable. By connecting the GenAI models to internal knowledge bases, the risk of outdated or inaccurate responses is reduced. This also helps GenAI to adapt to the operational context. Thus, RAG helps to make GenAI more useful and effective.

5.3.3 Organizational Structure

Technology needs an organizational structure to deliver strategic results. The first proposal is to establish an AI Steering Committee with executives and key function representatives, that will guide strategic plans, prioritize projects and oversee risks. Cross-functional teams are also vital for success, as GenAI affects multiple functions in an organization like marketing, operations, finance and HR. So, technical and operational leaders must work together. This helps knowledge to be shared and transferred across organization's different departments and prevents the creation of technological silos. Finally, systematic education is crucial for sustainable integration. Organizations must invest in upskilling and reskilling the employees. This includes training on AI basics, evaluating GenAI results and understanding its limitations. Training is not only for technical leaders but also for managers who make strategic decisions.

5.3.4 Adoption Roadmap

The successful integration of GenAI cannot be based on ideas or technology tests without a plan. Instead, a clear and gradual plan to adopt GenAI is needed, which includes experimentation, organizational learning, and slowly increasing its use. Based on the literature, this adoption plan can be broken down into four phases (Weinberg, 2025).

In the first phase, which is Strategic Assessment and Prioritization, the organization needs to figure out what GenAI can be used for and prioritize these uses based on how much of an impact they will have and how hard they are to be done. The goal here is not to start working on projects but to pick the ones that will give quick and measurable results, so companies can build momentum and gain experience with GenAI. At the same time, they need to check if their data infrastructure is ready and if their staff has the right skills.

The second phase is Pilot Implementation, where we develop and test GenAI applications in a controlled environment. It is very important to have rules in place, monitor how things are going, and get feedback from users at this stage. The tests here should be a way for organizations to learn and not one-time projects. The evaluation should include both quantitative indicators, such as how much time is needed for processes to complete and how much money are saved, and qualitative metrics, including if users trust GenAI, find it easy to cope with, and think it is valuable.

The third phase is Scaled Integration, where the tests are slowly made a part of the whole organization. At this point, organizations need to change how they work, adjust roles, and maybe move resources around. The transition from a test to using GenAI across the whole organization needs a good data system, clear rules on the use of GenAI and continuous training of the staff. This must be done step by step, while keeping an eye on risks and always evaluating how things are going.

The fourth phase is Continuous Optimization and Transformation, which recognizes that adopting GenAI is not a one-time thing but something that needs to keep working on. The organization needs to create a system to get feedback and use this feedback to improve GenAI with new data and user experience. Use cases also need to be re-evaluated in the terms of strategic objectives and technological developments. So, GenAI is no longer an innovation at this stage but integrated into the organizational structure and decision-making processes.

5.3.5 Key Performance Indicators (KPIs)

Successfully integrating GenAI into an organization requires more than simply adopting the technology. Organizations need to measure if GenAI is really helping them, if they are controlling its risks and if using GenAI leads to good outcomes that last. For this reason, Key Performance Indicators (KPIs) should measure both how well GenAI is working and if it is reliable.

First, companies need to look at how productive GenAI is making them. They can do this by measuring if it is taking time to finish tasks, if they are making more content or analytics, if they are making decisions faster and if they have less administrative work to do. They need to make this comparison related to how things were before starting using GenAI, so they can really understand what difference it is making and not overestimate what it can do.

Second, they need to calculate their cost savings either by not having to pay outsources or extra working hours for the staff to do tasks that GenAI is now doing. They also need to calculate how much money they save from having the right amount of inventories and not excess volumes. But they should not just look at how much money they are saving. They should also look at how much more value they are getting.

Third, organizations need to examine what happens when things go wrong with GenAI. They have to keep track of the results that GenAI gives and include bias or wrong information or when there is a problem with security or non-compliance with the rules. If they keep track of these incidents, they can make their rules and processes better and ensure that GenAI is working well and that people trust it.

Finally, organizations need to measure how satisfied their customers are with the use of GenAI. Companies can use GenAI in customer service, or to personalize offers and products, or to communicate with their consumers. So, they can measure customer satisfaction, which is an important indicator of their sustainable positioning, through Net Promoter Score (NPS) metrics, customer experience metrics or retention rates. The evaluation should consider if GenAI is really making things better for customers or just less personal.

5.4 Research Limitations

The present study, although based on a systematic review of the literature, has some limitations that must be considered when looking at the results. First of all, the research relied exclusively on secondary sources and not on primary empirical data. As mentioned in the relevant methodological section, the literature review is a synthesis and evaluation of already published material and does not produce new primary data. In addition, a literature review is not an empirical study that proves hypotheses or develops primary findings but organizes and interprets existing knowledge. Consequently, the conclusions of this research mainly reflect the theoretical and conceptual direction of the field and not verified results from quantitative or qualitative analysis of business cases. The absence of primary empirical evidence limits the possibility of generalizing the conclusions to specific organizational or sectoral contexts.

Secondly, the selection of articles was mainly based on the Google Scholar database and the relevance ranking logic, without a complete exhaustive record of all possible publications or a systematic search in multiple specialized databases. According to the guidelines for writing a literature review, it is necessary to state the scope of coverage and the inclusion and exclusion criteria of studies. However, each selection process inherently carries the risk of selection bias, as the final composition depends on the selected criteria and available sources. Therefore, it is possible that some relevant studies were not included in the final sample.

Thirdly, the field of GenAI is at a particularly early and rapidly evolving stage. The majority of the 2023–2025 publications are conceptual or normative in nature, with still limited evidence of long-term empirical studies. Since the literature review allows research gaps to be identified but does not fill them through primary analysis, the conclusions of the present study are mainly based on theoretical interpretation and early evidence. The long-term strategic impact of GenAI on the competitive performance of organizations remains under investigation and requires further empirical evidence.

Finally, research mainly adopts a strategic and administrative view, without systematic deeping into the technical, legal or psychosocial dimensions of technology. Although these dimensions are mentioned in the context of the analysis, they are not the central analytical focus of the study. Therefore, the conclusions mainly concern strategic management and the formation of a competitive advantage, and not the entirety of the technological, regulatory or societal implications of GenAI.

5.5 Future Research

The study's findings highlight significant opportunities for further research investigation, particularly because the current literature related to GenAI is characterized by fragmentation and limited empirical evidence. Firstly, empirical and particularly longitudinal studies are needed to examine the long-term impact of GenAI on economic performance, market share, and organizational learning. In this sense, it is proposed to monitor organizations over time with a "lifecycle" approach, that is from data options and training to deployment and feedback, to clarify when and under what conditions GenAI leads to a sustainable competitive advantage and not just short-term productivity gains (Surbakti, 2025). At the same time, the empirical verification of the proposed ethical frameworks is considered crucial, as a large part of the proposals remains theoretical and requires testing in real application conditions (Surbakti, 2025).

Second, it is necessary to create more complex strategic performance metrics that go beyond the traditional ones and capture intangible but strategically critical dimensions like organizational learning, creating new intellectual property, making good decisions, and building capacity. To do this, future studies can use tools that promote transparency, auditing and accountability. Examples of these tools include explainability mechanisms, auditing tools, and standardized impact assessment protocols. These tools are specifically designed for generative models, so that organizations can measure and document both the value and risks of integration (Surbakti, 2025).

Third, the study of human-AI collaboration in strategic environments is of particular interest including how executive roles change, which skills become critical (e.g., validation, governance literacy, crisis under uncertainty) and how accountability is affected. Here, the literature points to inclusive design approaches as a fruitful direction, where the evaluation and development of GenAI is done with the participation of multiple stakeholders, such as users, experts, legal and ethical advisors, and policymakers, in order to realistically capture the socio-organizational impacts of the technology (Surbakti, 2025).

Fourth, future research may examine industry differentiations through cross-domain comparisons, analyzing how GenAI impacts differently regulated sectors, such as finance or health, compared to less regulated industries, as ethical risks, compliance requirements, and governance mechanisms change substantially by scope (Surbakti, 2025). In this regard, the development of GenAI as a cross-border technology highlights the need for research around global governance and policy harmonization, given that issues such as deepfakes, disinformation, privacy, and intellectual property cannot be effectively addressed with fragmented national approaches (Surbakti, 2025). Finally, the connection of GenAI to sustainability and social value issues is an emerging field, where future studies can explore both the environmental impact of training and operating large models and the role of GenAI in social value creation, provided it is accompanied by measurable practices of responsible development and impact assessment (Surbakti, 2025).

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