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MSc Data Science in Business and Entrepreneurship

The Relationship of Generative AI Adoption with Firm Performance: Evidence from Text-Based Measures and Dynamic Capabilities Theory

Master's Thesis

Author:	Jesper Arts
Student ID:	2041304
Supervisor:	Dr. Plato Leung
Co-supervisor:	Dr. Ciro Esposito
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Abstract

Generative Artificial Intelligence (GenAI) has rapidly emerged as a potentially transformative, general-purpose technology with many different applications for business and with optimistic results. Yet, empirical evidence on its firm-level performance implications remains limited. This thesis investigates the association between GenAI adoption and company performance, with specific attention to the moderating roles of Dynamic Capabilities (DC) theory and industry heterogeneity. Using a text-based, bag-of-words approach, constructs of GenAI adoption and sensing, seizing and transforming dimensions of DC theory are operationalized. This is done through keyword analysis of corporate disclosures, more specifically, quarterly earnings call transcripts, from publicly listed firms in the S&P500 from 2018 to 2025. Performance is measured using both accounting-based (Return on Assets (ROA)) and market-based (Tobin's Q) indicators.

By employing fixed-effects panel regressions at the firm-year-quarter level, the anlaysis controls for unobserved time-invariant firm heterogeneity and macro-economic time shocks. Results indicate that binary GenAI adoption is positively associated with firm performance, with stronger effects for GenAI adoption intensity. Suggesting that deeper engagement with the technology relates with stronger performance gains. Results did not support the expectations that dynamic capabilities positively condition this relationship. The sensing capability even negatively moderates this relationship. Disclosures in the post-GPT stage show support for the positive moderation effects of knowledge-intensive industries on the GenAI-performance relationship.

This study contributes to literature by providing large-scale, disclosure-based evidence on GenAI adoption, extending Dynamic Capabilities theory to the context of GenAI by offering a nuanced insight into the temporal and organizational conditions under which GenAI adoption relates to firm performance, and extending Computer-Aided Text Analysis (CATA) literature by providing text-based constructs of GenAI and DC theory dimensions. From a practical perspective, the findings emphasize the optimistic potential of GenAI for business, possibly driving investment decisions, mainly, but not limited to, knowledge-intensive industries.

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Introduction

Since the introduction of AI some decades ago, it has gone through several development stages and AI winters to finally make its comeback in more recent years. Within this broader technological wave, generative AI (GenAI) has emerged as a potentially disruptive innovation. This technology refers to computational techniques that can generate seemingly new, meaningful content such as text, images, or audio from training data (Feuerriegel, Hartmann, Janiesch, & Zschech, 2024). It has emerged as a pioneering force in the AI landscape seeking to imitate, expand and even surpass human creativity and skills in knowledge-intensive fields (Sedkaoui & Benaichouba, 2024). This has led to 'hybrid intelligence', where human skills are complemented with by computer power, eventually outperforming individual agents, driving productivity growth (Dellermann, Ebel, Söllner, & Leimeister, 2019). With its broad range of implications for business and industries, it has begun to reshape industries, business models and sources of competitive advantage. Especially, since the introduction of Chat Generative Pre-Trained Transformer (ChatGPT) by OpenAI in 2022 (Fui-Hoon Nah, Zheng, Cai, Siau, & Chen, 2023), which has made the technology easily accessible to the wider, non-technically skilled, public. This has made GenAI adoption as fast as that of the personal computer (PC) three years after its launch and faster than the adoption of internet (Bick, Blandin, & Deming, 2024). GenAI applications have gained unprecedented attention from managers, policymakers, and investors. Currently, 71% of organizations regularly use GenAI in at least one business function, which comes from 65% in early 2024 (Alex, Alexander, & Larena, 2025), and ChatGPT has recently reached 700 million weekly active users, representing almost 10% of the global population (Chatterji et al., 2025).

Grey literature from global consultancy companies and policy institutions have similar optimistic, forward-looking views in which they see the transformative potential in GenAI and expect large productivity gains for business, resulting in increased financial results (Alex et al., 2025; World Economic Forum & PwC, 2024). GenAI is forecasted to grow $7 trillion in global gross domestic product (GDP) and contribute to an increase in productivity of up to 1.5% (Rana, Pillai, Sivathanu, & Malik, 2024). However, there is little, scalable objective evidence on how the adoption of GenAI affects firm performance. Executed research on the association of GenAI adoption with company performance mostly used constructed adoption measures that rely on surveys, interviews or case studies which are prone to the self-reporting bias, and which is not scalable across thousands of firms. And whilst GenAI adoption in business is not merely decision to use a technology, it is part of a firm's broader capability to sense opportunities, seize them, and transform their operations to facilitate its successful adoption. This link between Dynamic Capabilities (DC) theory and the technology adoption of GenAI has been minimally examined, especially on an objective, scalable basis. As DC theory is mostly examined through case studies, interviews and surveys in literature. Managers have made GenAI adoption decisions without knowing how and if it would lead to performance increase (Sánchez, Calderón, & Herrera, 2025). Whilst we now observe firms across different industries experimenting with GenAI for different purposes: from marketing and customer engagement to product development and operational efficiency (Sedkaoui & Benaichouba, 2024). And as with earlier general-purpose technologies, GenAI diffusion across firms and industries is likely to be uneven (Sharma, Dwivedi, Metri, Lal, & Elbanna, 2024). Therefore, consistent, objective adoption measures offer scalability to measure whether and how GenAI adoption influences performance and to make cross-industry comparisons. This enables managers to make well-informed GenAI technology investment decisions. Also, because of the rapid advancements of GenAI and its rapid integration into business practices, academic research on the effects of GenAI for business has fallen behind (Obschonka & Fisch, 2022). Without systematic measures of adoption and DC theory, both academic inquiry and managerial decision-making risk being driven more by hype than by evidence.

The objective of this thesis is to investigate the association of generative AI adoption with company performance, and to which extent this relationship is being moderated by dynamic capabilities and differs by industry. By performing text analysis to corporate disclosures of publicly listed firms, this study develops systematic, scalable and replicable measures of GenAI adoption and sensing, seizing and transforming dimensions of dynamic capabilities theory. This leads to the following research question: **How does Generative AI adoption relate with firm performance, and how do Dynamic Capabilities and industry characteristics moderate this relationship?** To address this research question, the following hypotheses are formulated:

- **H1a.** Firms that adopt Generative AI will show higher firm performance compared to periods in which they have not adopted GenAI, ceteris paribus.
- **H1b.** Greater Generative AI adoption intensity within a firm is positively associated with firm performance.

- **H2a.** Within firms, increases in sensing capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H2b.** Within firms, increases in seizing capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H2c.** Within firms, increases in transforming capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H3a.** The positive association between generative AI adoption and firm performance is stronger for firms operating in knowledge-intensive industries than for firms in non knowledge-intensive industries.

This thesis focuses on publicly listed U.S. firms in the S&P500 index, as these provide both consistent reliable disclosure data and standardized performance indicators. The period of analysis covers 2018 to 2025, a study period including both pre- and post-ChatGPT release. Data of corporate disclosures, such as quarterly earnings conference call transcripts, and financial performance data such as Return on Assets (ROA), Tobin's Q, and firm controls come from the Refinitiv Database (Refinitiv, 2025). Generative AI adoption is defined as references to and discussion of generative AI terms and constructed using text-based detection from earnings call transcripts, which reflect real-time managerial communication, strategic priorities and expectations. Dynamic capabilities dimensions are similarly operationalized through keyword and concept-based text analytics, defined as the ability of a firm to sense opportunities, seize them, and transform their operations. Industry characteristics are based on the Global Industry Classification Standard (GICS). Quantitative, empirical analysis is done through fixed effects regressions using panel data to measure GenAI adoption association with firm performance, including moderating factors of DC theory and industry classifications. This research, however, does not assess the internal validity of implementation; that is, the study does not distinguish between mere mentioning of GenAI or DC terms or active GenAI integration and DC capabilities. Out of scope are non-listed firms, investor sentiment analysis, factors driving adoption decisions and broader societal or ethical implications of GenAI adoption.

This thesis contributes to both theory and practice. From a theoretical perspective, it enriches the literature on GenAI and firm performance, by providing a systematic, scalable measure of adoption and its analysis on performance. Similarly, it enriches literature on Dynamic Capabilities theory by constructing a scalable, text-based measure of sensing, seizing and transforming capabilities and introduces the theory into the domain of GenAI technology. It has contribution to strategic management methods, where it adds to the usage of earnings call transcripts as a scalable data source for management research. From a practical perspective, the findings provide strategic managers and investors with insights whether GenAI investments translate into measurable performance increase and how organizational dynamic capabilities strengthen or weaken these effects. Investors and policymakers may replicate the developed GenAI adoption measure to monitor technological engagement across sectors and geographical regions at large scale and assist in the evaluation of GenAI diffusion impact for companies.

The remainder of this thesis is structured as follows. Chapter 2 reviews the relevant literature on the technology of Generative AI and Dynamic Capabilities. Chapter 3 outlines the methodology, including data sources and transformation decisions, dictionary construction, transcript scoring, and statistical modeling. Chapter 4 presents descriptive results on GenAI adoption and DC theory across industries and analyzes their statistical relationship with firm performance. Chapter 5 discusses the findings considering theory and research, and Chapter 6 concludes with contributions, limitations, and avenues for future research.

Literature Review

2.1 Theoretical Background

2.1.1 AI versus GenAI

The field of Artificial Intelligence (AI) has come a long way since the formal introduction of the term by McCarthy, Minsky, Rochester, and Shannon (1955) in the 1950s. Back then, models were 'rule-based', meaning they contained hard-coded logic that explained what to do if something happened, but these were not generalizable and sufficient for real-world complex problems (Cao et al., 2023). With the rise of 'machine learning' (ML) in the 1980s and 1990s this shifted to probabilistic models that could learn patterns, including the early forms of 'neural networks' (NN's). But these had computational limitations and lack of data; problems which were later resolved in the 2010s with the rise of 'deep learning'. Where 'convolutional neural networks' (CNN's) and 'recurrent neural networks' (RNN's) transformed and revolutionized image recognition and 'natural language processing' (NLP) respectively (Cao et al., 2023). Generative adversarial networks' (GAN's) were put forward in 2014 as a novel generative model (Goodfellow et al., 2014) . They consist of two competing NN's, the generator and the discriminator. The generator produces as realistic data as possible while the discriminator tries to differentiate synthesized data from real data. In 2017, Vaswani et al. (2017) introduced the 'transformer' model which set the stage for a new approach to process sequential data, which led to dramatic improvements in machine summarization and text generation and laid the foundation for 'large language models' (LLM).

Since the introduction of AI, it went through several development stages and AI winters to finally make its comeback in more recent years with the introduction of Chat Generative Pre-Trained Transformer (ChatGPT) by OpenAI in 2022, a large language model that is built upon the transformer framework (Fui-Hoon Nah et al., 2023). These unsupervised machine learning models use deep learning techniques for training on massive amounts of data. With the rise of these new mathematical models, the ability of AI to perform discriminative modelling tasks like classification or prediction has shifted to generative modelling. These models aim to infer some actual data distribution and by doing so, they can produce new synthetic samples (Feuerriegel et al., 2024). This enables them to fulfil tasks in a human-like matter, creating novel content by learning complex patterns in data (Feuerriegel et al., 2024). This made their model pass the 'Turing test' designed by Turing (1950) in 1950, meaning that it was indistinguishable from human-created content.

This new type of AI has been given the term 'Generative AI' (GenAI). It refers to computational techniques that can generate seemingly new, meaningful content such as text, images, or audio from training data (Feuerriegel et al., 2024). It has emerged as a pioneering force in the AI landscape seeking to imitate, expand and even surpass human creativity and skills in knowledge-intensive fields (Sedkaoui & Benaichouba, 2024). Some exemplary GenAI models are ChatGPT or LLaMA for text, Midjourney or DALL-E for images and DeepBrain for videos (Feuerriegel et al., 2024; Fui-Hoon Nah et al., 2023). They completely shift digital interactions and enable human-like assistance with increased performance (Sedkaoui & Benaichouba, 2024). By its presentation in a chat form, the technology of GenAI can be easily collaborated with by a wider, also non-technical, public. This has led to a concept called 'hybrid intelligence', where human skills are complemented with by computer power which enhances strategic decision-making and problem-solving capabilities, and which therefore eventually outperform individual agents (Dellermann et al., 2019). This has led to a fast spread of the technology throughout society.

Because GenAI is easily accessible and can complement human knowledge and skills, we see many different applications of it within business in different sectors (Mondal, Das, & Vrana, 2023). For example, GenAI has the capabilities to assist in marketing and sales, creative content production, product development, operations, risk and legal, human resources, accounting, finance, customer service, coding and planning jobs, and business model development (Sedkaoui & Benaichouba, 2024). Showcasing its broad potential to support human talent and by doing so, lead to innovations, generating new income streams, minimizing need for manual effort in routine tasks and increasing efficiency and effectiveness which leads to increased profitability (Feuerriegel et al., 2024; Fui-Hoon Nah et al., 2023; Rana et al., 2024). But at the same time, these studies emphasize the existence of challenges and concerns regarding job displacement, biases, privacy, copyright and environmental pollution. This emphasizes the need for ethical and regulatory frameworks for safe adoption of GenAI (Rana et al., 2024; Sedkaoui & Benaichouba, 2024).

To compare, traditional machine learning models are typically trained on labelled datasets for specific, predefined tasks such as image recognition, fraud detection or demand forecasting (Cao et al., 2023). Whilst generative AI is built on great amounts of heterogenous, largely unlabelled data (Fui-Hoon Nah et al., 2023). These learn broad data structures that enable general-purpose reasoning and can be applied to multiple tasks, such as novel content generation (Feuerriegel et al., 2024). Therefore, GenAI is a novel form of AI that shifts itself from task-specific systems towards flexible, generalizable models capable of supporting wide range of organizational processes (Sedkaoui & Benaichouba, 2024). The open-source chat format in which the technology is presented, simplifies interaction with it for the broader public and therefore driving its fast and increased adoption in society (Bick et al., 2024). They state that GenAI adoption is as fast as that of the personal computer (PC) three years after its launch and faster than the adoption of internet. Whilst like the PC, observing higher adoption amongst educated, young, and high-wage workers.

To summarize, the recency, immense power, fast development, widespread availability and increased adoption in several business processes of GenAI together make it an interesting and appropriate technology of focus for this thesis with promising impact on company performance. For this, we should ground the concept into theory to theoretically understand its adoption and performance outcomes.

2.1.2 GenAI in Theoretical Frameworks

The widespread adoption of GenAI across businesses and industries is explained by Obschonka and Fisch (2022), who mention GenAI to be part of a concept called 'transformative AI', which relates to the use of AI tools that have such inherent capabilities that they could induce societal transitions, like that of the industrial revolution. The disruptive innovation theory provides a theoretical lens to position GenAI as such a technology, disrupting the current market situation, opening up entirely new markets and business models (Christensen & Overdorf, 2000). These technologies change the way value is created and challenge the established market leaders. This helps to explain why firms tend adopt or struggle with adoption of GenAI, a technology of the disruptive type. Christensen and Overdorf (2000) also emphasize how established companies can fail to effectively respond to emerging technologies. Because they first appear to be inferior, firms rather have focus on sustaining innovations, which are incremental improvements to existing products or services, and must integrate tools into complex existing company structures. Coccia (2024) states that GenAI provides products or processes that satisfy the needs currently demanded by the mainstream market and therefore classifies as disruptive. Christensen (2008) add that the challenge of adoption of a disruptive innovation for established firms is not just about foreseeing the arrival of the technology but also about their existing resources, processes and values making firms incapable to respond. Sánchez et al. (2025)

mention that disruptive innovations often entail high failure rates and uncertain short-term returns. Opposed to sustaining innovations, disruptive innovations can even open up entirely new markets and business models (Christensen & Overdorf, 2000). Generative AI can be seen as both a disruptive and sustaining innovation.

Firms tend to differ in timing and intensity of GenAI adoption. The dual theoretical perspective of the Diffusion of Innovations (DoI) theory (Rogers, 1983) and Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) help to contextualize GenAI adoption through both the process-oriented (DoI) and the organization-oriented (TOE) lens. From the DoI theory, relative advantage, compatibility with existing practices, and trialability and observability of results positively impact GenAI adoption. Whilst perceived complexity has a negative effect (Albishri, Rai, Attri, Yaqub, & Walsh, 2025; Khan, Mehmood, & Khan, 2025; Nawaf Alka'awneh, Abdul-Halim, & Md. Saad, 2025; Rath, Tripathy, & Jain, 2024; Sánchez et al., 2025; Wael AL-khatib, 2023). This explains that perceived advantages such as efficiency, creativity and innovation; alignment with existing software infrastructure and data-driven workflows; and the trial ability, to do pilots and proof of concepts; help to reduce uncertainty and drive for GenAI adoption. By analyzing through the three contexts of the TOE-framework, organizations can make better strategic decisions for the selection and implementations of technologies like GenAI. Organizations with present technological readiness, such as digital maturity and infrastructures; organizational factors such as management support, skills, resources and innovation culture; and environmental influences like competitive pressure, regulation, customer demand, governmental support, open-access LLM's and responsible AI; help to reduce risk and drive GenAI adoption (Kumar et al., 2025; Nawaf Alka'awneh et al., 2025; Rath et al., 2024; Reddy, Gotur, & Bhat, 2025; Sánchez et al., 2025; Wael AL-khatib, 2023). Rogers (1983) categorizes firms into five groups based on their willingness to adopt an innovation: innovators, early adopters, early majority, late majority, laggards. Which range from fast adoption to the latest adopters respectively.

GenAI adoption can logically result into firm performance. The Resource-Based View (RBV), first introduced by Wernerfelt (1984) but later significantly developed by Barney (1991), explains that internal resources and capabilities of a company are the main drivers for its competitive advantage and long-term success, shifting the business strategy focus from external markets. For firms to obtain a sustained competitive advantage, resources or capabilities must be Valuable, Rare, Inimitable and Non-substitutable (VRIN). Resources can be either tangible, like data or an infrastructure, or intangible, like knowledge or routines. In the context of GenAI, the theory of the RBV explains that adoption alone does not guarantee increased performance, but rather its value comes from how effectively firms integrate it into their existing resources. As the technology is widely available, adoption of the technology in itself might not immediately be rare nor inimitable, but when embedded within firm-specific routines and resources, such as customer service automation, code generation, or product design, GenAI becomes a VRIN resource and acts as a complement to existing human and technological assets, thereby generating productivity gains and competitive advantage (Singh, Chatterjee, & Mariani, 2024). Prior literature has found that GenAI enhances both exploitative and explorative innovation, that is, the ability to automate existing processes and create new respectively (Singh et al., 2024). Firms that successfully adopt GenAI can realize substantial performance improvements, particularly when the technology is aligned with sectoral characteristics and use-case relevance (Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug, & Tchatchouang Wanko, 2020). And deeper use of new technologies leads to stronger value creation (Kane, Palmer, Phillips, Kiron, & Buckley, 2015).

Together, these theoretical perspectives help to explain the technology of GenAI, its adoption and how its many applications for business would logically associate with increased performance for business. This gives rise to the first hypotheses which are distinguished in GenAI adoption as mere interaction with the technology and as interaction intensity, trying to capture thorough engagement with the technology:

- **H1a.** Firms that adopt Generative AI will show higher firm performance compared to periods in which they have not adopted GenAI, ceteris paribus.
- **H1b.** Greater Generative AI adoption intensity within a firm is positively associated with firm performance.

2.1.3 Dynamic Capabilities Theory

These theories however, do not fully explain the organizational mechanisms through which firms convert GenAI adoption into sustained performance outcomes. Dynamic Capabilities (DC) theory, on the other hand, provides a comprehensive framework for understanding exactly this (Teece, Pisano, & Shuen, 1997). It explains why some firms with strong dynamic capabilities are able to effectively sense a technology coming, seize their opportunity by its adoption and even transform their organizational processes to be able to successfully adopt GenAI and enjoy increased performance benefits over others who do not possess these capabilities and struggle with successful adoption. For this thesis, DC theory is therefore chosen as the primary conceptual lens as it gives promising theoretical foundation to explain the GenAI-performance relationship.

The Dynamic Capabilities (DC) theory builds upon the RBV to address the difficulty of explaining how firms sustain a competitive advantage in rapidly changing environments. A limitation of the RBV which Teece et al. (1997) addressed by explaining how firms maintain competitive advantages by their ability to sense, seize, and transform their resources. More thoroughly explained, sensing refers to the ability to identify, interpret, and anticipate. It involves scanning, learning and monitoring activities that allow firms to detect shifts in customer needs, emerging technological developments or potential disruptions. These capabilities allow firms to recognize opportunities and assess their strategic relevance. Seizing refers to the capability to mobilize resources to address the opportunities revealed. It involves making strategic choices, designing business models, make investments, and coordinate assets. This includes the selection of technologies to invest in, whilst evaluating the option under uncertain financial returns. Lastly, transforming is the capability reconfigure and transform the organizational structure. This includes reallocation of its asset base and restructuring routines to integrate new technologies. These support long-term adaptability to changing environments (Teece, 2018; Teece et al., 1997). Dynamic capabilities are considered to incorporate those processes that enable organizations to sustain superior performance over time (Wilden, Gudergan, Nielsen, & Lings, 2013). Dynamic capabilities differ from operational capabilities. Operational capabilities enable the organization to perform an activity on an ongoing basis using more or less the same techniques, whilst dynamic capabilities on the other hand, are directed towards strategic change to align the organization with a rapidly changing environment (Wilden et al., 2013).

For the rapidly, technologically changing business environment due to the rise of GenAI specifically, this theory entails that firms with strong dynamic capabilities can fully enjoy its benefits. Whereas firms having limited dynamic capabilities may adopt GenAI superficially, achieving limited or short-lived benefits of the technology. It is the organic structure of a firm that facilitates the impact of dynamic capabilities on organizational performance (Wilden et al., 2013). Bughin (2024) emphasizes that GenAI performance gains are conditional on the capabilities of the firm and their complementary resources. Consistent with DC theory, they show that performance outcomes depend on the ability to combine the technology with existing data, skills, governance and organizational transformation. The capability to interact with GenAI can be seen as a dynamic capability in itself too, that strengthens entrepreneurial effectiveness, which leads to both direct and indirect increased firm performance (Cui, 2025). Additionally, Wamba-Taguimdje et al. (2020) conceptualize AI capabilities as dynamic capabilities that enable organizations to sense, seize and transform. They do not show that AI directly improves performance by default, but instead, AI capabilities influence firm performance through organizational agility and innovation. Protogerou, Caloghirou, and Lioukas (2012) criticize the direct effect of DC theory on firm performance. They state that dynamic capabilities refer to the transformation of operational capabilities of a firm, and therefore, their impact on performance is mediated by operational capabilities. So, it is the operational capabilities that can create competitive advantage, not the dynamic capabilities directly. Overall, DC theory gives insight into how a firm can successfully gain a competitive advantage and performance gains in a rapidly changing environment. This is highly suitable to the specific technology of GenAI which, as explained before, is rapidly changing business environments. Therefore, this indicates that a firms dynamic capabilities are currently essential in this environment to sense a technology like GenAI and seize their opportunity and transforming their current organizational structure and processes to capture its promising implications for firm performance. This gives rise to the following hypotheses:

- **H2a.** Within firms, increases in sensing capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H2b.** Within firms, increases in seizing capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H2c.** Within firms, increases in transforming capabilities strengthen the positive association between GenAI adoption and firm performance.

2.1.4 Industry Heterogeneity

As described before, GenAI has the potential to complement human knowledge in many different applications and in different industries, explaining its wide adoption (Mondal et al., 2023; Sedkaoui & Benaichouba, 2024). Where as with earlier general-purpose technologies, GenAI diffusion across firms and industries is likely to be uneven (Sharma et al., 2024). We have said that GenAI alignment with existing sectoral-specific resources and processes, to complement existing human and technological assets, is important to realize performance gains (Singh et al., 2024; Wamba-Taguimdje et al., 2020). Whilst present resources such as existing data, infrastructure, skills and knowledge are essential to its successful adoption (Bughin, 2024; Wael AL-khatib, 2023). Therefore, we likely observe industry heterogeneity in GenAI adoption and firm performance. Where studies often find stronger performance gains of GenAI in knowledge-intensive industries like information technology, health care, finance and communication services, whilst more asset-intensive industries like energy, utilities, materials and industrials often show weaker relationships (Eisfeldt, Schubert, & Zhang, 2023; European Central Bank., 2025; Huang & Lin, 2025; Jia, Li, Ma, & Xu, 2024; Mbanyele, 2025; Reddy et al., 2025). Knowledge-intensive industries rely more heavily on symbolic reasoning, analytics, software and expert decision-making which are directly enhanced by GenAI, whilst asset-intensive industries rely more heavily on physical capital, logistics and supply chain, where the knowledge automation of GenAI has weaker direct impact. This gives rise to the last hypothesis:

- **H3a.** The positive association between generative AI adoption and firm performance is stronger for firms operating in knowledge-intensive industries than for firms in non knowledge-intensive industries.

2.2 Related Work

2.2.1 State of The Field

Let us now discuss (grey) literature on the current state of the field of Generative AI to investigate what its adoption rates are, how its diffusion is uneven across regions and industries, for what purposes it is used in which industries and already shortly touch upon some performance results.

The technology of GenAI is nowadays increasingly being adopted in businesses due to its ease of use, application possibilities and strengths (Rana et al., 2024). To get a first, large-scale measure of GenAI adoption at work, Bick et al. (2024) performed a national survey in which they found a GenAI adoption rate of almost 40% across U.S. adults, and 23% reported usage of the technology at work in the week prior to the survey. With the highest use in the North American region (Chui, Yee, Hall, Singla, & Sukharevsky, 2023). As explained before, one of the major applications using the technology of GenAI, ChatGPT, has recently reached 700 million weekly active users, representing almost 10% of the global population (Chatterji et al., 2025). In a global survey study of Chui, Hazan, et al. (2023), more than 30% of responding companies report to use Generative AI in at least one business function, and larger companies are adopting faster and more comprehensively (Alex et al., 2025). GenAI release has increased the largely uneven adoption of AI technology across firms, where cross-country gaps in Europe reaching from

2% to 14% in 2021, have gone to 4% to 28% in 2024 (Kergroach & Héritier, 2025). GenAI usage skews towards higher-income, English-proficient, service-oriented economies. And younger individuals have a higher GenAI exposure (Alex et al., 2025).

As for a regional analysis, Europe tends to fall behind on the United States (US) and China in various dimensions of AI. For example, in 2023, the U.S. private investment in AI was around 62 billion euro, followed by a 7 billion of China, whilst Europe only had an approximate 9 billion euro all together (Madiega & Ilnicki, 2024). Also, the venture capital investment in GenAI tends to fall behind. This results in the fact that 73% of LLMs is being developed in the US, another 15% in China, whilst the EU companies are struggling to release such kind of technology. Also, regarding GenAI adoption, we see around 40% adoption in the U.S. whilst in Europe, this is only 30% (Sukharevsky et al., 2024). And in an OECD report (Kergroach & Héritier, 2025), rising AI adoption differences between regions, sectors and firm sizes are mentioned.

As for industry differences, regular GenAI adoption at work is highest in technology, professional services and financial industries and lower in advanced Industries, energy and healthcare industries. GenAI adoption is highest in knowledge-intensive sectors and lowest in asset-heavy sectors (Alex et al., 2025; Bick et al., 2024; Calvino, Haerle, & Liu, 2025; Reddy et al., 2025)

As for use case differences, overall, companies mostly use GenAI in marketing and sales, product or service development, and service operations. Whereas the usage percentage is lowest in manufacturing, followed by supply chain management and human resource (HR) Alex et al. (2025); Chui, Hazan, et al. (2023); Eloundou, Manning, Mishkin, and Rock (2024).

As per combination of industry and use case, the most frequent GenAI use cases in different industries appear to be the following: usage for knowledge management in professional service industries; usage for software engineering in Technology firms; usage for sales and marketing in consumer goods firms; usage for strategy and risk in finance; usage for product development in healthcare; and usage for service operations and support in media and telecom (Alex et al., 2025). Aligned with Alex et al. (2025), Salih et al. (2025) resulting from their extensive literature review, list more specific, common GenAI use cases across industries and resulting from that, different performance gains such as time savings, cost savings or product increases. These use cases are: customer service and automated trip planning in tourism & travel; customer support, fraud detection, predictive analysis and stock forecasting in banking & finance; scheduling, reporting and risk assessment in construction; coding, debugging and documentation in software solutions; inventory forecasting, route optimization, traffic safety and predictive maintenance in supply chain & transportation; and content creation, campaign optimization, sentiment analysis and email marketing in digital marketing & social media. Iqbal, Shafqat, Krishna, and Rauf (2024) discuss industry 4.0 and 5.0, about AI automation and human-AI collaboration respectively. They observe GenAI usage for procurement and scenario simulation in supply chain companies, usage for product recommendation and virtual fashion models in E-commerce & retail companies, usage for design optimization, prototyping and human resource management in manufacturing companies and usage for drug discovery and adverse event detection in pharmaceuticals & healthcare. All in all, we see a wide range of applications in different industries.

Overall, grey literature from global consultancy companies and policy institutions foresee exponential gains resulting from the technology. They have optimistic, forward-looking views in which they see the transformative potential in GenAI and expect large productivity gains, resulting in increased financial results. GenAI could impact 40% of global working hours and significantly boost productivity by automating routine tasks and augmenting complex tasks. Jobs will be mostly augmented through human-machine collaborations, only few will be fully replaced. Barriers to adoption are lack of trust, skills or unclear return on investment evidence (World Economic Forum & PwC, 2024). GenAI could add 2.6 to 4.4 trillion dollars to the global economy across 63 different use cases. Approximately 75% of the potential is in customer operations, marketing and sales, software engineering and Research and Development (R&D). And the most affected industries are potentially banking, retail, technology, pharmaceuticals and life sciences. With less impact on the manufacturing sector (Chui, Hazan, et al., 2023). Related to the transforming capability of DC theory, 21% of GenAI adopters said that at least some workflows in their business had fundamentally been redesigned due to the technology adoption (Alex et al., 2025). They state that redesigning workflows is the strongest driver for Earnings Before Interest and Tax (EBIT) impact resulting from GenAI, where 17% of organizations report that GenAI contributed to over 5% of EBIT over the past year (Alex et al., 2025). Important is to state that these forward-looking projections are not empirical firm-level evidence, although valuable for understanding managerial expectations. But they are meant to complement academic findings with industry expectations, not to be treated as empirical proof. For the latter, we will now investigate the existing body of academic, empirical literature closely related to our research.

2.2.2 Existing Body of Literature

Now that we have set a conceptual background and the current situation of GenAI, let us investigate the existing body of academic, empirical literature, closely related to our research about the association of GenAI adoption with company performance and the mediating roles of Dynamic Capabilities (DC) theory and different industries.

The existing body of literature shows plentiful research on GenAI and company performance, with the application of different theoretical frameworks, methodologies and scopes. Very closely related to our research is the paper of European Central Bank. (2025) published through the European Central Bank (ECB) who performed text analysis on quarterly earnings call transcripts form the S&P 500 companies between 2014 and 2024. This research provides great guidance for our research as they have developed a successful methodological framework to measure GenAI adoption from public disclosures and directly investigated its relationship with company performance, whilst making a distinguishment between early adopters and laggards. Their results showed that companies early adopting GenAI showed higher excess quarterly returns than laggards and higher stock price increases post-ChatGPT. They also tried to make industry-level comparisons even though they mention their sample size limited statistical power. This resulted in statements that early exposed firms in the IT, consumer services or consumer discretionary sectors experienced larger stock price gains. This paper gives great guidance to our research, providing evidence to measure GenAI adoption from conference call transcripts using text analysis and effectively examine its impact on company performance. Additionally, closely related research entails that of Jia et al. (2024), who provide early evidence on how firms respond to the emergence of GenAI through text analysis of managerial communication in conference calls and filings using keyword detection for mentions, Loughran & McDonald lexicon for sentiment and ChatGPT-4 for classification of action initiatives. They mention upcoming mentions of GenAI in conference calls following ChatGPT's release, of which mainly positive statements that call for action of integration or investment. Discussions were stronger in firms with more patent filings, cybersecurity threats, labor exposure to AI and customer-facing operations. Results showed tech and service sectors show far greater engagement whilst energy and utilities show minimal reaction. Furthermore, they show positive abnormal returns and higher trading volume after GenAI discussions, mainly driven by positive tone and initiative-related talk. Their findings indicate that GenAI is perceived as a strategic opportunity rather than a threat, and that such discussions come with positive market reactions, suggesting that investors recognize the potential of GenAI adoption.

Mbanyele (2025) did text analysis of SEC 10-Q filings in the U.S., to identify GenAI-related term frequencies like “ChatGPT” or “Copilot” in publicly listed non-financial firms across multiple industries from 2021 to 2023. Using DiD and panel fixed affects regression it was found that GenAI exposure significantly enhances investment efficiency. These firms show stronger growth opportunities measured by Tobin’s Q post-ChatGPT release. They make industry comparisons by telling us that industries with high information asymmetry the effects are the strongest. Furthermore, Cui (2025) investigates the moderating role of GenAI in the effect of entrepreneurial motivations, both opportunity-based and necessity-based, on performance. This was done via OLS and DiD on survey data of top managers across 1396 Chinese companies from 2018 to 2023. By measuring performance using ROA as main measure but ROE, Tobin’s Q and sales growth for robustness checks, they have found that the ability to interact with GenAI positively impacts firm performance, mediated by innovation and knowledge acquisition. They showcase results are stronger for high-tech industries. Eisfeldt et al. (2023) have constructed a novel, firm-level GenAI exposure index based on occupational data from O*NET, in which ChatGPT-3.5 performed task-scoring based on likely GenAI exposure. These constructed measures were validated with GenAI mentions in earnings call transcripts. By means of event study, portfolio analysis and regression, they found firms with higher GenAI exposure to experience significantly positive abnormal stock returns following the release of ChatGPT. Suggesting that investors anticipate on the value gains of the technology. The strongest effects were shown in information, publishing and finance sectors. In their bachelor’s thesis, Bekmagambetova, Uderbay, and Yeslyamova (2024) investigate the impact of public GenAI adoption announcements on stock prices for major firms in the technology sector, using both event studies and regression analysis with no clear impact result. They did not find significant effects for GenAI adoption announcements to drive stock prices in either short- or long-term. Also, the event study showed mixed or neutral abnormal returns and the regression revealed that stock prices were primarily driven by quarterly earnings instead of GenAI announcements. Lee, Dabirian, McCarthy, and Kietzmann (2020) have found by doing a randomized field experiment on an online platform that GenAI complements existing services rather than substitutes them, leading to higher user engagement, revenues and profits of it.

Although not specifically focused on public companies, Khan et al. (2025) investigate TOE factors that influence manufacturing firms’ adoption of GenAI and its impact on organizational performance using survey data in China. They find that GenAI adoption enhances both exploratory and exploitative innovation and that exploratory innovation mediates the positive effect of GenAI on company performance. This is an important finding related to our research, as this suggests that the positive impact of GenAI on company performance happens through the ability of the company to experiment, innovate, and explore new opportunities. Singh et al. (2024) found similar results in their survey of IT and R&D firms in India. Additionally, Rana et al. (2024) have investigated senior professionals from the IT sector in India by means of a survey. They have found significantly positive effects of several different institutional and ethical factors on the use of GenAI; and additionally, a positive effect of GenAI adoption on organizational performance, controlled for by firm size and whilst using organizational innovativeness as a moderator as well. However, firm size appeared to be insignificant. Otis, Clarke, Delecourt, Holtz, and Koning (2025) investigate the impact of GenAI adoption on financial performance by means of a field experiment amongst entrepreneurs in Kenia. They find different results between high- and low-performing entrepreneurs based on how well they tailored the advice of GenAI. They showed that firm-level performance for SMEs can be highly uneven. Focused on over eleven thousand European SMEs and AI, Ardito, Filieri, Raguseo, and Vitari (2024) have found using a survey-based AI adoption indicator, that AI adoption significantly and directly enhances SME revenue growth. SMEs adopting have a 12.6% lower chance of turnover decline and 15.1% higher chance of growth larger than 30%. Specifically focused on the retail and manufacturing sectors, Haider and Faisal (2024) have found a 20% increase in sales for retail SMEs and a 30% lower downtime and 25% defect reduction for manufacturing SMEs. As from a literature review and case studies, AI appeared to drive operational efficiency, decision-making and competitiveness. Reddy et al. (2025) made clear industry comparisons using a multiple case study analysis on SMEs, using both surveys and interviews on companies in healthcare, manufacturing, finance and retail sectors. They found the following adoption rates and performance results: 85% adoption in healthcare leading to 15% diagnostic accuracy and -20% admin time; 80% adoption in Finance leading to -25% fraud and -18% financial losses; 65% in Retail leading to 10% customer engagement; 60% in manufacturing leading to 20% production efficiency. They say healthcare and finance lead adoption rates, because they are data-intensive, due to complex data processing needs and high return potential. Successful adopters achieve 25% ROI. Efficiency gains differ significantly, from 12% in healthcare to 6% in retail. Technological readiness is the most important factor for successful adoption, followed by management support and investment. Early adopters have high tech readiness and investment.

Although not specifically focused on financial performance, through another survey with over ten thousand respondents in the U.S., a first nationally representative estimate of GenAI adoption has been achieved by Bick et al. (2024). In which self-reported use frequencies and time savings measured that almost 27% of workers used GenAI and this led to non-financial performance increases of 5.4% time savings in work hours and an aggregate productivity gain estimate of 1.1%. Like previously mentioned research of Khan et al. (2025) and Rana et al. (2024), Wael AL-khatib (2023) also finds several factors using the TOE framework that significantly impact GenAI adoption by using a survey on managers and employees in Jordanian retail companies. Although the match with adoption and performance is not made, a significantly positive effect of GenAI adoption on both exploratory and exploitative innovation has been found. Bapat, Malik, Garg, Thirlangi, and Gopalsamy (2025) have shown that GenAI improves strategic decision-making effectiveness and adaptability, using the World Management Survey Manufacturing dataset covering 2004 to 2014. Using a survey dataset from Chinese manufacturing firms, Li, Zhu, Chen, and Liu (2024) have found that GenAI enhances economic, social and environmental supply chain performance. As it appears to drive efficiency, carbon reduction and circularity when embedded in green collaborations. Furthermore, Bughin (2024) focused on how and why firm-level productivity gains vary across industries, using large global survey dataset with 110 Generative AI firms and 1165 firms with AI strategies across domains of content creation, coding, marketing and sales and customer service. By doing OLS and econometric modelling, they have found average efficiency gains of 20.1% and quality improvements of 21.8%. Where the top firms account for most of the gains. They mention data resources and AI skills to be the main drivers for this performance increase. And they mention early adopters to be more productive.

Although not specifically focused on GenAI, Furthermore, Liu (2024) used text analysis on earnings call transcripts from 2006 to 2024 and SEC filings from 2016 to 2022 of U.S. public firms to construct a text-based AI exposure measure using GPT-3.5-turbo and GPT-4o-mini, which they validated using labor-based exposure measures. They used event studies and DiD regressions to link their measure to labor and performance changes with a focus on pharma and software industries. They have found that firms with AI exposure have lower labor costs, higher ROE, higher market valuations and higher gross margins. They even mention that AI exposure via communication data captures strategic intentions and productivity gains earlier than labor data does. Huang and Lin (2025) performed research on how AI adoption affects firm performance for 300 firms in the S&P 500 from 2010 to 2017. They found 50 AI adopters and 250 non-adopters by performing news analysis and after leaving out IT firms on purpose to avoid bias. By means of Ordinary

Least Squares (OLS) regressions on firm-level data, they found that AI adopters show higher financial performance and having significantly higher market value. Although the effect on productivity gains is positive, they appear to be statistically weak. Interestingly, they also investigate the first-mover advantage, showing that they did receive short-term profit advantages but had higher implementation costs and inefficiency in asset usage. And they showed that industries of retail and finance were better AI performers, although this reflected negatively in market values. Wamba-Taguimdje et al. (2020) did a large-scale case study on major AI solution providers like Nvidia and AWS which spread across multiple global sectors. Using RBV and DC theory, they have found that AI capabilities have significant positive impacts on process and organizational performance. Where the financial sector reached up to 80% cost reduction and 10% revenue growth, the healthcare sector had a 69% drop in transcription costs and 12% higher case-mix index, and the oil & gas industry had 75% time reduction and improved decision accuracy. Where they state that AI acts as both an efficiency enhancer and innovation enabler, driving new business models and process redesign.

2.3 Critical Analysis and Research Gap

After investigating closely related work, summarizing scopes, methods used, measures for adoption and performance and key findings, we will now critically analyse similarities and differences, limitations of previous research and the gap that remains.

2.3.1 Critical Analysis

The reviewed studies show a growing consensus that AI, and more specifically GenAI, enhance firm performance through various channels. Whether it is done through driving exploratory and exploitative innovation; (Khan et al., 2025; Rana et al., 2024; Singh et al., 2024; Wael AL-khatib, 2023; Wamba-Taguimdje et al., 2020) efficiency enhancement; (Bughin, 2024; Haider & Faisal, 2024; Li et al., 2024; Reddy et al., 2025; Wamba-Taguimdje et al., 2020) investment efficiency; (Mbanyele, 2025) opportunity- and necessity-based entrepreneurial motivations; (Cui, 2025) complementing existing services; (Lee et al., 2020) early adopting; (European Central Bank., 2025; Huang & Lin, 2025); or improved decision-making and competitiveness (Haider & Faisal, 2024); they all seem to discuss the widespread application and positive impact of GenAI for business. And whether measured financially, by Return on Assets (ROA), Tobin's Q, abnormal returns (CARs), stock prices or annual returns; or non-financially, by efficiency or productivity increases; if significant effects are present, they seem to be positive. However, research differs in examining whether the performance effects are direct, stemming from the deployment of the technology, or indirect, mediated through previously mentioned variables.

From a theoretical perspective, most empirical studies are anchored in frameworks such as TOE, DoI, or RBV, and only a subset explicitly adopts the Dynamic Capabilities lens (Bughin, 2024; Khan et al., 2025; Wamba-Taguimdje et al., 2020). Even when DC concepts are present, such as exploratory and exploitative innovation as mediators (Khan et al., 2025; Singh et al., 2024) or innovation and knowledge acquisition (Cui, 2025), they are not systematically integrated into a coherent firm-level model, combining GenAI adoption, capabilities and performance.

Studies repeatedly show mixed magnitudes in firm performance which appear context dependent, being heterogeneous per industry. Technology, information, publishing, finance and certain consumer and service sectors often show stronger performance gains (Eisfeldt et al., 2023; European Central Bank., 2025; Huang & Lin, 2025; Jia et al., 2024; Mbanyele, 2025; Reddy et al., 2025), while energy, utilities and some traditional sectors show weaker reactions. Moreover, the industry is typically treated as a control variable, dummy, or descriptive grouping rather than as a theoretically grounded moderator with clear expectations about which industries should benefit more and why.

Also, we see that there is no standardized methodology for measuring GenAI adoption, potentially explaining difference in results. Methodologies differ from self-reported survey or interview data (Ardito et al., 2024; Bick et al., 2024; Bughin, 2024; Haider & Faisal, 2024; Khan et al., 2025; Li et al., 2024; Rana et al., 2024; Singh et al., 2024) to case studies (Reddy et al., 2025; Wamba-Taguimdje et al., 2020), experiments, text analysis (European Central Bank., 2025; Liu, 2024; Mbanyele, 2025), patent-based indicators (Jia et al., 2024), or labour-based indicators (Eisfeldt et al., 2023).

Furthermore, studies show several limitations. Where some research is limited in scope, focusing on specific sectors, such as manufacturing (Ardito et al., 2024; Bapat et al., 2025; Haider & Faisal, 2024; Khan et al., 2025; Lee et al., 2020) or IT (Singh et al., 2024); regions, such as the U.S., China, or India; time spans, including both pre- and post-ChatGPT release; or firm sizes, large publicly listed, private, SMEs or non-commercial. Resulting in studies mentioning limited sample sizes, having insufficient data for conclusions with statistical power and raising questions on generalisability across listed firms and global industries.

2.3.2 Research Gap

To conclude, the reviewed academic literature agrees on the perceived potential of GenAI and shows empirical evidence on its positive impact on company performance. Grey literature mirrors these optimistic projections and acknowledges GenAI to be a technology with disruptive potential. However, study results seem to show heterogeneity through various mediating factors and across industries. This leaves room for additional empirical investigation on how GenAI adoption associates with increased firm performance. Additionally, few research has shown to systematically integrate theoretical constructs into a firm-level GenAI-performance model. Whilst as discussed, Dynamic Capabilities theory is a promising theory to explain performance differences for firms in rapidly changing environments, such as that of GenAI. Additionally, dynamic capabilities theory has yet to be examined using a systematic, objective, text-based measure. This offers consistent scalability opportunities and enables replication of research. Therefore, this study aims to fill this gap by investigating the relationship between generative AI and performance whilst including dynamic capabilities theory and industry-specific context as mediating factors. This offers strategic managers and investors a deeper understanding of the tangible value of GenAI and Dynamic Capabilities in specific industrial context, guiding them to make informed strategic decisions for investment in the technology of GenAI and to operationalize sensing, seizing and transforming capabilities.

By constructing text-based measures for Generative AI adoption and Dynamic Capabilities theory, this research also extends the existing text analysis research, providing additional evidence for the ability to extract theoretical variables from text using a well-validated methodological pipeline. Additionally, it contributes to the literature on Dynamic Capabilities theory by applying its dimensions to the immersive technology of GenAI and its resulting impact on business performance. Lastly, it contributes to literature on GenAI, that according to Obschonka and Fisch (2022) has fallen behind.

2.4 Research Questions and Hypotheses

To summarize the literature review, the technology of GenAI has been explained. We have placed it in several theoretical constructs of which Dynamic Capabilities has been selected as the most relevant. We have explained the current state of the field regarding GenAI adoption and investigated closely related research. This showed increasing adoption rates and promising implications for company performance using using different scopes and research methodologies. We have discussed their similarities and contradictions, emphasizing the growing consensus of GenAI enhancing firm performance, different GenAI adoption measures and methods and different magnitudes of results and industry heterogeneity. This has left a research gap to examine and the goal for this thesis. To conclude, this thesis aims to: objectively measure GenAI adoption and DC theory dimensions using text analysis; measure the association of GenAI adoption with firm performance; investigate the mediating role of DC theory on the GenAI-performance relationship; and investigate the mediating role of knowledge-intensive industry context. Therefore, the research question of this thesis is: "**How does Generative AI adoption relate with firm performance, and how do Dynamic Capabilities and industry characteristics moderate this relationship?**" With the sub-questions being: "How is Generative AI adoption associated with firm performance?"; "To what extent do a firm's Dynamic Capabilities (sensing, seizing, transforming) strengthen the relationship between GenAI adoption and performance?"; "Does the effect of Generative AI adoption on performance differ between knowledge-intensive and non knowledge-intensive industries?" For this thesis, the hypotheses have been discussed to be:

- **H1a.** Firms that adopt Generative AI will show higher firm performance compared to periods in which they have not adopted GenAI, ceteris paribus.
- **H1b.** Greater Generative AI adoption intensity within a firm is positively associated with firm performance.
- **H2a.** Within firms, increases in sensing capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H2b.** Within firms, increases in seizing capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H2c.** Within firms, increases in transforming capabilities strengthen the positive association between GenAI adoption and firm performance.
- **H3a.** The positive association between generative AI adoption and firm performance is stronger for firms operating in knowledge-intensive industries than for firms in non knowledge-intensive industries.

Methodology

3.1 Research Design

This study adopts a quantitative archival research design to examine how Generative AI adoption affects firm performance in the S&P 500. The analysis relies on publicly available corporate disclosures, more specifically, earnings call transcripts, which are key channels through which firms communicate technological investments, strategic priorities, and organizational changes. Text analysis is used to extract the following constructs from these disclosures: Generative AI adoption, and the three dimensions of Dynamic Capabilities, that is, sensing, seizing, and transforming. These text-based measures are combined with financial performance data in a panel regression with firm and year-quarter fixed effects. This design enables a systematic and replicable investigation of the relationship between GenAI adoption and performance while accounting for unobserved firm-level heterogeneity.

3.2 Data Sources

The empirical analysis focuses on firms included in the S&P 500 index, which provides a stable and consistent sample of large, publicly traded U.S. companies with comprehensive disclosure requirements. These firms are particularly suitable for studying Generative AI adoption because they participate regularly (quarterly) in earnings calls, allowing for consistent text-based measurement across years. Liu (2024) mentions that AI exposure via communication data captures strategic intentions and productivity gains earlier than labour data does, which is why variable construction following from text analysis is more appropriate than to use job exposure to GenAI scoring. The sample period is from 2018 to 2025, which is after the rise of transformer models in 2017 (Vaswani et al., 2017), which, as described before, laid the foundation for large language models. And it covers the period of the release of ChatGPT in late 2022 (Fui-Hoon Nah et al., 2023), which caused further rise and diffusion of the technology. With that, this period covers both the emergence and the diffusion of Generative AI technologies and aligns with the period in which firms began disclosing AI-related strategies.

Data was collected from Refinitiv (2025) into four datasets; a masters table collecting the most recent company ID's (RIC-code), names, founded years and GICS industries for companies in the S&P500 index; a table collecting financial and accounting data for every firm-year-quarter combination necessary for construction of the performance indicators; a table collecting financial and accounting data for every firm-year-quarter combination necessary for construction of the control variables; a table containing all earnings conference call transcripts for all companies in the S&P500 from 2018 to 2025.

3.3 Data Cleaning and Preprocessing

The collected earnings conference call transcript data are downloaded in plain-text format and converted to analysable text using a custom parsing script. To ensure consistency across firms and years, all documents undergo the same preprocessing workflow. This first entails the removal of structural noise present in Refinitiv transcripts, such as the elimination of boilerplate disclaimers, Refinitiv header and footer material, corporate participant names, bracketed operator instructions, speaker labels. These are standard components across transcripts and provide no meaningful linguistic content and would therefore inflate total document word counts, and therefore the intensity measures. Secondly, this remaining conference call text went through basic text cleaning steps such as lowercasing, removal of punctuation, numbers, special characters and whitespace normalization. This remaining text consists of the prepared remarks of the management and the analyst questions and answers, which together reflect the importantly, relevant linguistic content for detecting GenAI and DC theory language. Finally, the cleaned text is split into individual words, 'tokens', which is essential for our 'bag-of-words' approach, as keyword matching and counting operates at the token level. No stemming or lemmatization is applied to avoid altering the semantic content of domain-specific terms (e.g., "model," "models," "modeling"). However, as explained later, to ensure all words are correctly captured, 'Regex' patterns are applied to the dictionaries. The resulting cleaned text serves as the basis for constructing keyword frequencies for Generative AI adoption and Dynamic Capability measures. The preprocessing pipeline ensures transparency, replicability, and comparability in the text-based variables across all firm-quarter observations.

The four previously mentioned tables of data collected from Refinitiv, that is, the master data, dependent variable data, control variable data and text scoring variable data; were combined into one dataset with 16.502 observations. This dataset included empty values, zero's and data discrepancies due to joining tables and missing data from Refinitiv (2025). Discrepancies existed due to merging 524 different companies in the transcript data table, with the 503 companies in the most recent S&P500 master table and for which we also got the performance and control variables. Therefore, the transcript data included companies that have left the S&P500 index over the years. These excessive companies (1.711 rows) were removed to only keep the most recent S&P500 company list. Furthermore, duplicate files appeared to be extracted which were removed. Additionally, there appeared to be multiple firm-year-quarter duplicates (158 rows) because there were sometimes different, separate calls held on the same day or on a date in the same quarter but relating to a different fiscal period. These duplicated keys are aggregated into one row containing the mean for transcript intensity scores and the maximum for the binary adoption score. The variable of R&D and all its variants in Refinitiv (2025) appeared to have over 50% missing data and was therefore chosen to be excluded from the model. Other missing data from Refinitiv (2025) in the performance or control variables were removed, resulting in an acceptable dataset reduction of approximately 10%. From this dataset, variables were constructed as defined in the next sections. From these, incorrect data from Refinitiv (2025), which resulted in negative firm ages, has been removed. This resulted in the final dataset containing all variables used for regression analysis.

3.4 Variables and Measures

3.4.1 GenAI adoption

Generative AI adoption is operationalized using a dictionary-based text analysis approach. This approach follows literature in Computer-Aided Text Analysis (CATA) (Kindermann et al., 2021; McKenny, Aguinis, Short, & Anglin, 2018; Short, Broberg, Cogliser, & Brigham, 2010). By doing so, the dictionary was constructed through a structured, multi-step process combining both deductive dictionary creation, including theoretical grounding and synonym expansion, and inductive dictionary expansion. For this, OpenAI's ChatGPT (OpenAI, 2025) was used as an auxiliary tool to accelerate parts of the deductive and inductive refinement steps. Specifically, in the deductive phase, it was used to aggregate terminology of relevant academic sources uploaded to make theoretical definitions of the constructs. In the synonym extension phase, it helped to accelerate the process by analyzing relevant seed terms out of an exhaustive list of synonyms. In the inductive step, it again helped to accelerate the process by analyzing an exhaustive list of relevant inductively acquired terms from the corpus. Importantly, all exhaustive lists and AI-generated suggestions were manually reviewed, validated and either accepted or rejected based on theoretical definitions from DC and GenAI literature. This process remains fully replicable without AI usage but may be prone to human biases.

First, short theoretical construct definitions were written based on existing recent studies analyzing GenAI disclosures in corporate communications (Bekmagambetova et al., 2024; Cui, 2025; Eisfeldt et al., 2023; Eloundou et al., 2024; Jia et al., 2024; Mbanyele, 2025). After which the dimensionality of the construct is assessed, following the approach of Short et al. (2010). Where GenAI adoption is defined as a unidimensional construct. Because, although firms mention GenAI in different linguistic forms such as technology names (*"LLM," "generative ai"*), use-cases (*"chatbot," "automation"*), or strategy statements (*"genai implementation"*), these expressions all represent the firm's engagement with GenAI. Therefore, a single comprehensive dictionary is used shown in Appendix A.1, rather than separate dimensions. Secondly, a preliminary deductive dictionary was constructed by reviewing academic literature on GenAI technologies and terminology, such as the recent studies analyzing GenAI disclosures in corporate communications (Bekmagambetova et al., 2024; Cui, 2025; Eisfeldt et al., 2023; European Central Bank., 2025; Jia et al., 2024; Mbanyele, 2025) and based on technical vocabulary of corporate AI disclosures. From these sources, core terms were extracted closely related to the construct definition, including: *generative AI, gen ai, LLM, large language model, transformer model, foundation model, fine-tuning, Chat-GPT*, with the full list visible in Appendix A.1. Thirdly, to broaden coverage of terminology, additional synonyms were created using the NLTK WordNet tool (Bird, Klein, & Loper, 2009; Miller, 1995). This helped to explore verbal stems and related terms. However, because WordNet does not capture modern AI terminology, and often returns irrelevant, non-domain synonyms, all additions required manual curation. Where appropriate, word stems were included to capture linguistic variations. Fourth, following Short et al. (2010), inductive dictionary expansion was done. The reason for this is that deductive lists may miss out on sector-specific jargon and emergent phrasing. An inductive step goes over seed terms in the actual text data using a rolling window to investigate words close to the seed term. For this, all transcripts were loaded, unique uni grams and bigrams occurring more than three times were extracted. At first, this resulted in an exhaustive list of irrelevant stop words and morphological variants. These were filtered out and the frequency was raised. From this reduced candidate list with more relevant terms, candidates were reviewed and words closely related to the theoretical construct were added. Fifth, 'regex' terms were added to the dictionaries to capture all variants of a term in the text scoring phase. This resulted in the final dictionary in Appendix A.1. Then all transcripts were scored using two operationalizations:

- **GenAI Adoption (Binary)** Defined as 1 if one or more GenAI terms appear in a firm–quarter transcript, and 0 otherwise. This measure captures whether the firm signals any GenAI-related activity (extensive adoption).

- **GenAI Adoption Intensity** Calculated as:

$$\text{GenAI Intensity} = \frac{\text{GenAI keyword frequency}}{\text{total words}} \times 100,$$

  providing a length-normalized measure of how intensively GenAI terms appear in conference call transcript. The multiplication by 100 icnreases interpretability of the variable. A common normalisation approach as explained in text analysis literature (Kindermann et al., 2021; Short et al., 2010). This ensures that the variable is interpretable in percentages. It is the percentage of GenAI term mentions as a share of the entire conference call length in words. This reflects the degree to which a firm engages with the technology.

Together, these two indicators capture both the presence and the prominence of Generative AI in firm disclosures.

3.4.2 Dynamic Capabilities

Dynamic Capabilities were operationalized using text analysis following the exact same methodological approach of Short et al. (2010) as described before. For these constructs, the theoretical definitions were based on the theory introduced by Teece et al. (1997) and Teece (2018). The dimensionality of the construct was assessed, resulting in the three foundational dimensions of Dynamic Capabilities theory: sensing, seizing, and transforming. For each dimension, a dictionary of relevant terms is constructed based on the theoretical definitions shown in Appendix A.1. Then, conference call transcripts were scored using this dictionary to get the following variables:

- **Sensing Capability** Reflects a firm's ability to identify new opportunities and monitor technological or market trends. The dictionary includes terms related to exploration, market scanning, innovation and opportunity recognition. The score is computed as:

$$\text{Sensing Score} = \frac{\text{sensing-related terms}}{\text{total words}} \times 100,$$

  providing a length-normalized index of how strongly a firm communicates sensing activities, interpreted in percentages.

- **Seizing Capability** Captures a firm's ability to mobilize resources, make strategic investments, and commit to technological opportunities. The dictionary includes terms referencing investment, deployment, resource allocation, commercialization, and strategic commitment. The score is computed as:

$$\text{Seizing Score} = \frac{\text{seizing-related terms}}{\text{total words}} \times 100,$$

  providing a length-normalized index of how strongly a firm communicates seizing activities, interpreted in percentages.

- **Transforming Capability** Reflects organizational change, process reconfiguration, and restructuring required to integrate new technologies. The dictionary includes terms related to change management, process redesign, reconfiguration, and organizational restructuring. The score is computed as:

$$\text{Transforming Score} = \frac{\text{transforming-related terms}}{\text{total words}} \times 100,$$

  providing a length-normalized index of how strongly a firm communicates transforming activities, interpreted in percentages.

These three variables provide measures of how strongly each firm signals their dynamic capabilities in its disclosures.

3.4.3 Firm Performance

Research of Huang and Lin (2025) states that firm performance can be investigated through three lenses: financial performance (Return on Assets, Return on Equity, profits, earnings, etc.), productivity (Cobb-Douglas production function) or market value (Tobin's Q). For this thesis, firm performance is measured through both an accounting-based and a market-based indicator commonly used in financial performance research (Cui, 2025; Kindermann et al., 2021; Short et al., 2010). The primary measure will be:

- **Return on Assets (ROA)** This is an accounting-based performance measure. ROA measures how efficiently a firm uses its asset base to generate profits. Defined as:

$$\text{ROA} = \frac{\text{Net Income}}{\text{Total Assets}},$$

- **Tobin's Q** Tobin's Q is used as an additional performance measure for robustness checks. This is a market-based performance measure. This captures forward-looking expectations of firm value. Tobin's Q is widely used in technology adoption research (Cui, 2025; Haider & Faisal, 2024; Mbanyele, 2025). Defined as:

$$\text{Tobin's Q} = \frac{\text{Market Capitalization}}{\text{Total Assets}},$$

3.4.4 Industry

The knowledge intensive industry classification is a binary variable based on the high-level GICS sector names. More specifically, this variable entails:

- **Knowledge Industry (Binary)** The industry classification variable is either 1, if firms belong to the GICS sectors of Information Technology, Communication Services, Financials or Health Care and is 0 otherwise. This means that non knowledge intensive sectors are: Industrials, Consumer Discretionary, Consumer Staples, Utilities, Real Estate, Materials, Energy.

3.4.5 Control Variables

To isolate the effect of GenAI adoption and Dynamic Capabilities, the models include several firm-level controls known to influence performance (Cui, 2025; European Central Bank., 2025; Jia et al., 2024; Kindermann et al., 2021; Short et al., 2010). The controls for this thesis entail:

- **Firm Size** Measured as the natural logarithm of total assets.
- **Firm Age** Calculated as the current year minus the year of founding.
- **Leverage** Defined as total debt divided by total assets.
- **R&D Intensity** Measured as research and development expenditure divided by total revenue.
- **Capital Expenditures** Defined as capital investments of the firm.

3.5 Statistical Analysis

After construction of the panel dataset, the analytical process follows. Steps in the analysis include description of the data, performing validation checks on the created dataset, run diagnostic tests, testing hypotheses running regressions and test for robustness and reliability of results. Analysis is done using panel data techniques consistent with the firm year-quarter structure of the dataset.

3.5.1 Descriptive Statistics

Descriptive statistics are reported for all variables, including means, standard deviations, and pairwise correlations. These provide an overview of the distribution of Generative AI adoption, Dynamic Capability scores, and performance indicators across the sample. These give insights into any unexpected data patterns such as error nous values which are appropriately dealt with. Such as setting negative firm ages due to wrong data from Refinitiv (2025) to zero. Correlation heat maps are constructed which allow preliminary assessment of associations amongst key constructs. They provide basis for some construct validation tests described later.

3.5.2 Diagnostic Checks

Before estimating the regression models, the data are examined for potential issues such as multicollinearity and non-normality. Variance Inflation Factors (VIF) are used to assess multicollinearity among independent variables. Variable distributions are shown in violin plots and histograms for numeric and categorical variables respectively. These give clear insight in data distributions and show which variables need to have their skewness or outliers handled to improve modelling in a later phase. This led to winsorizing the dependent variables of ROA and Tobin's Q and log transforming CapEx to handle skewness and improve modelling.

3.5.3 Baseline Regression

As we are dealing with panel data, which combine cross-sectional variation, between firms, with time-series variation, within firms over time. Compared to purely cross-sectional or time-series models, panel regressions offer three key advantages that are particularly relevant to this thesis. First, firms largely differ in unobservable characteristics that may influence both GenAI adoption and firm performance such as managerial quality, organizational culture and technological orientation. A panel regression allows to control for this so-called 'unobserved heterogeneity'. Secondly, this allows for within-firm observation over time. As for this thesis, we are interested in observing whether a change in GenAI adoption within a firm is associated with a change in performance. Rather than comparing completely different firms, with completely different revenue and asset structures, we are interested to see how a firm can benefit from GenAI adoption. Thirdly, by explicitly modelling firm-specific effects, the omitted variable bias is reduced which would otherwise arise if time-invariant firm characteristics were omitted.

The primary empirical tests rely on ordinary least squares (OLS) regression with firm and year-quarter fixed effects (FEOLS). This specification controls for time-invariant firm characteristics and common macroeconomic shocks while estimating the association between GenAI adoption, Dynamic Capabilities, and firm performance. Standard errors are clustered at the firm level to address serial correlation. This can be seen as that a firm has its own intercept. Alternative modelling options could be a pooled OLS regression, which would treat all observations as independent and ignore individual and time-specific differences; a Random-Effects (RE) model, which would assume that firm-specific effects are uncorrelated with explanatory variables; or a first-difference model that would remove firm fixed effects by modeling changes between consecutive periods; and dynamic panel models which include lagged dependent variables. Although the latter seems a valid option to include, this model requires stronger assumptions and valid instruments, whilst it increases complexity that may affect interpretability. Therefore, FEOLS is chosen as the statistical analysis method.

3.5.4 Regression Models

The association of Generative AI adoption with firm performance is estimated using two baseline fixed-effects models that separately evaluate binary adoption (`H1a`) and adoption intensity (`H1b`).

Model 1a: Binary GenAI Adoption (H1a)

$$\text{Performance}_{it} = \beta_0 + \beta_1 \text{GenAIAdopt}_{it} + X_{it}\beta + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{3.1}$$

where:

- Performance_{it} is the firm's performance measure (ROA or Tobin's Q),
- GenAIAdopt_{it} is a binary indicator equal to 1 if a Generative AI term appears in the transcript of firm i at time t,
- X_{it} is a vector of control variables,

- α_i denotes firm fixed effects,
- γ_t denotes year fixed effects,
- ε_{it} is the error term.

`H1a` predicts $\beta_1 > 0$.

Model 1b: GenAI Adoption Intensity (H1b)

$$\text{Performance}_{it} = \beta_0 + \beta_1 \text{GenAIIntensity}_{it} + X_{it}\beta + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{3.2}$$

where:

- $\text{GenAIIntensity}_{it}$ is the normalized frequency of Generative AI keyword occurrences as a share of total words in the transcript times 100 words to be interpretable in percentages.

`H1b` predicts $\beta_1 > 0$.

Model 2: Dynamic Capabilities as Moderators (H2a–H2c)

To incorporate Dynamic Capabilities, the extended model examines whether sensing, seizing, and transforming capabilities moderate the relationship between Generative AI and firm performance. This specification tests hypotheses `H2a-H2c`.

$$\begin{aligned}\text{Performance}_{it} = {} & \beta_0 + \beta_1 \text{GenAIAdopt}_{it} + \beta_2 \text{Sensing}_{it} + \beta_3 \text{Seizing}_{it} + \beta_4 \text{Transforming}_{it} \\ & + \beta_5 \left(\text{GenAIAdopt}_{it} \times \text{Sensing}_{it}\right) + \beta_6 \left(\text{GenAIAdopt}_{it} \times \text{Seizing}_{it}\right) \\ & + \beta_7 \left(\text{GenAIAdopt}_{it} \times \text{Transforming}_{it}\right) + X_{it}\beta + \alpha_i + \gamma_t + \varepsilon_{it}.\end{aligned} \tag{3.3}$$

where:

- Sensing_{it} is the normalized frequency of sensing-related Dynamic Capability keywords as a share of total words in the transcript, multiplied by 100 to be interpretable as percentages.
- Seizing_{it} is the normalized frequency of seizing-related Dynamic Capability keywords as a share of total words in the transcript, multiplied by 100 to be interpretable as percentages.

- Transforming_{it} is the normalized frequency of transforming-related Dynamic Capability keywords as a share of total words in the transcript, multiplied by 100 to be interpretable as percentages.

This formulation allows the analysis to assess whether firms that exhibit stronger Dynamic Capabilities strengthen performance outcomes when adopting or intensifying their use of Generative AI. `H2a` predicts $\beta_5 > 0$, `H2b` predicts $\beta_6 > 0$, and `H2c` predicts $\beta_7 > 0$. This model is investigated with both `GenAIAdopt` and `GenAIIntensity` as an alternative variation.

Model 3: Industry Heterogeneity as Moderator (H3a)

Finally, industry-level heterogeneity is examined by interacting GenAI adoption with the binary knowledge-intensive industry variable. This includes heterogeneity between knowledge-intensive industries and non knowledge-intensive industries in the model and investigates how this moderates the relationship between Generative AI and firm performance to test hypothesis `H3a`.

$$\begin{aligned}\text{Performance}_{it} = \beta_0 &+ \beta_1 \text{GenAIAdopt}_{it} + \beta_2 \text{KnowledgeIndustry}_i \\ &+ \beta_3 \left(\text{GenAIAdopt}_{it} \times \text{KnowledgeIndustry}_i\right) \\ &+ X_{it}\beta + \alpha_i + \gamma_t + \varepsilon_{it}. \end{aligned} \tag{3.4}$$

where:

- $\text{KnowledgeIndustry}_i$ equals 1 for firms in knowledge-intensive GICS sectors (IT, Financials, Health Care, Communication Services) and 0 for firms in asset-intensive sectors (Energy, Materials, Industrials, Utilities).

`H3a` predicts $\beta_3 > 0$, indicating a stronger positive association of GenAI adoption with company performance in knowledge-intensive industries. Again, this model is investigated with both `GenAIAdopt` and `GenAIIntensity` as an alternative variation.

3.6 Reliability and Validity

The derived textual-based variables undergo five validation stages as defined by Short et al. (2010). That is, content validity, external validity, dimensionality, discriminant validity and predictive validity. Additionally, the model is internally validated and model robustness checks have been performed. These validation results are described later-on in Chapter 4.

3.6.1 Content Validity

Content validity assesses whether the dictionary adequately represents the full theoretical domain of the construct created. This can be done by comparing word lists with word lists in existing literature or by using experts to review the dictionaries and apply 'inter rater agreement' (Kindermann et al., 2021; McKenny et al., 2018; Short et al., 2010). Although precautions have been taken to construct theoretically sound dictionaries, as has previously extensively been described, by following established procedures for construct development in computer-aided text analysis (CATA) (Kindermann et al., 2021; McKenny et al., 2018; Short et al., 2010), content validity is limitedly assessed in this thesis. Exhaustive lists of seed terms in the deductively created and inductively extended dictionaries have been scanned by ChatGPT (OpenAI, 2025) to speed up the process. The AI-generated suggestions were manually reviewed and validated which gives rise to human bias in the methodological process. Additionally, although present in closely related research, the dictionary was not compared to existing GenAI dictionaries and no experts were asked to review due to time constraints of thesis completion.

3.6.2 External Validity

External validity examines whether the dictionary produces expected results across different samples, settings or time periods, demonstrating its generalizability. This can be done by comparing score distributions between different subsamples, in which, as defined by Short et al. (2010), meaningful similarities or differences should be demonstrated. In CATA literature, this is exemplified by comparing scoring results across different data sources. For this thesis, this could imply to compare conference call transcript scores with annual report scores. However, due to time constraint of thesis completion, that comparison is left out. However, external validity is tested between different time and industry subsamples of the panel dataset. Meaningful similarities or differences are explained by comparing results of the text-based variables across pre- and post-GPT stages and between knowledge and non-knowledge intensive industries to examine if the dictionaries have produced expected results.

Additionally, a random sample of transcripts is manually inspected to verify contextual correctness of dictionary hits, partially addressing specific-factor error as identified by McKenny et al. (2018). If feasible, large language models (LLMs) are explored as an auxiliary check to identify potential false positives or false negatives and to compare human–machine agreement.

3.6.3 Dimensionality

Following theory from Short et al. (2010), this stage checks whether the dictionaries created for each dimension manage to measure distinct but related variables, therefore validating the dimensionality of each construct. Correlations between dimensions should not be excessively high but also not near zero. To assess dimensionality, correlation structures across the DC indices and GenAI scores are examined. This does not apply to the constructed variable of GenAI as it was discussed to be unidimensional. However, the variable is also compared with the DC dimensions to provide evidence of discriminant validity. This would suggests that the created variables are meaningfully different concepts. Although we have defined DC terms to be logical dimensions of dynamic capabilities of a firm, theory explained them to be theoretically distinct constructs (Pavlou & El Sawy, 2011; Protogerou et al., 2012; Teece, 2018; Teece et al., 1997; Wamba-Taguimdje et al., 2020; Wilden et al., 2013). Therefore, we can expect some low correlations between dimensions.

3.6.4 Discriminant Validity

Discriminant validity assesses whether the dictionary is empirically distinct from unrelated constructs. This is done through testing correlations of the text-based variables with unrelated variables, such as the controls. They should show that created variables are distinct from other variables and can therefore safely added to the model without adding multicollinearity.

3.6.5 Predictive Validity

The final validation phase as described by Short et al. (2010) is measuring predictive validity. This is actually done by running the planned empirical regressions in Chapter 4, where we test whether the text-based variables are able to predict theoretically relevant outcomes in the expected direction.

3.6.6 Model Validity

As explained, to mitigate concerns about omitted variable bias, all regression models include firm fixed effects and year-quarter fixed effects. Firm fixed effects control for unobserved, time-invariant characteristics such as managerial quality, corporate culture, or strategic orientation. Year-quarter fixed effects control for macroeconomic conditions that affect all firms. Standard errors are clustered at the firm level to correct for serial correlation in longitudinal text-based measures. Model fit is evaluated by investigating within R^2, which measures the proportion of within-firm variation over time in firm performance explained by the model. Traditional R^2 is usually high in fixed-effect regressions controlled for both firm and year-quarter fixed effects. Whereas within R^2 is more appropriate for fixed-effects models because it excludes the between-firm variation that is absorbed by firm fixed effects. Additionally, joint significance and consistency of signs are investigated.

3.6.7 Model Robustness

Coefficient stability was assessed by several robustness checks and model comparisons. Firstly, the models are regressed using both the binary and intensity GenAI adoption variables. Secondly, the accounting-based performance variable in the main model is swapped with the market-based variable of Tobin's Q. Thirdly, models were estimated on different subsamples, including both the full 2018 to 2025 sample and a post-GPT release (2022) subsample. These model alterations allow for checking the stability of results. Standard errors were clustered at the firm level to account for serial correlation and heteroskedasticity. Sequential model extension was used by expanding the baseline model with dynamic capabilities variables and interaction terms. This allows to check stability of the signs and magnitudes of core GenAI coefficients.

3.7 Ethical Considerations

This study relies exclusively on publicly available corporate disclosures and financial data, including earnings call transcripts and financial accounting data from Refinitiv (2025). As no personal, confidential, or sensitive individual-level information is used, the research does not pose privacy or data protection risks. All text processing and analysis are conducted following academic standards, with complete transparency regarding variable construction and methodological choices. The design does not involve human subjects or experiments and therefore does not require ethical review or informed consent procedures.

3.8 Limitations

Despite the strengths of the research design, several methodological limitations should be acknowledged. Firstly and most importantly, the dictionary-based text analysis approach captures the presence and frequency of predefined terms but cannot fully reflect the contextual meaning or strategic intent in the disclosures. Although the dictionaries were developed using a structured deductive and inductive procedure, combining theory-based term selection, synonym expansion, and inductive refinement, firms vary substantially in how they articulate technological initiatives and display dynamic capabilities. Consequently, textual indicators remain indirect representatives for underlying organizational actions and may miss context-specific nuances, such as whether a GenAI mention reflects experimentation, implementation, or just strategic signalling. There has not been experimented with additional scoring methods such as usage of llm's to better capture the constructs in earnings calls transcripts due to time constraints of the thesis. And as explained, content and external validity lack additional checks.

Secondly, although firm and year-quarter fixed effects solve many concerns about unobserved heterogeneity, they cannot account for all time-varying factors that may influence both disclosure behaviour and performance. Such as competitive shocks and regulatory changes may co-occur with the technology adoption but remain unmeasured.

Thirdly, statistical analysis is done using fixed-effect OLS only, no additional regressions have been experimented with to compare results or to allow for the research to make causal conclutions.

Fourth, the analysis is limited in scope to S&P 500 firms, which constrains generalizability of results. And large, publicly traded firms differ from smaller firms in resources, disclosure quality, and strategic communication practices. As a result, the conclusions may not extend to private firms, SMEs, or companies outside the U.S. context like that of Europe, which document differently. However, the S&P 500 is a widely studied benchmark group, and its transparency makes it well suited for disclosure-based research. The methodological pipeline can still be extended to corporate firms with similar publicly disclosed data.

Results

4.1 Descriptive Statistics

4.1.1 All Variables

Variable	Mean	StdDev	Min	Q1	Median	Q3	Max
ROA (%)	9.269	7.653	-51.500	4.150	7.800	12.850	84.500
Tobin's Q	2.410	2.903	0.031	0.760	1.487	2.877	50.036
GenAIAdopt (0/1)	0.100	0.299	0.000	0.000	0.000	0.000	1.000
GenAIIntensity (% of words)	0.006	0.035	0.000	0.000	0.000	0.000	0.802
Sensing (% of words)	0.399	0.169	0.000	0.285	0.399	0.508	1.382
Seizing (% of words)	0.247	0.107	0.022	0.170	0.230	0.305	0.932
Transforming (% of words)	0.059	0.058	0.000	0.020	0.042	0.079	0.586
FirmSize (log assets)	23.911	1.265	19.887	23.030	23.852	24.701	28.513
FirmAge (years)	37.444	30.508	0.000	17.000	28.000	47.000	143.000
Leverage	0.320	0.245	0.000	0.191	0.300	0.415	3.892
CapEx (bn USD)	1.844	4.441	0.003	0.197	0.561	1.658	82.999
KnowledgeIndustry (0/1)	0.426	0.494	0.000	0.000	0.000	1.000	1.000

Table 4.1: Descriptive statistics for all variables used in the empirical analysis (N = 12,902). Dictionary-based variables are expressed as a percentage of total words. CapEx is reported in billions of USD.

The final panel dataset consisted of 12,902 rows of firm-year-quarter observations from 2018 to 2025. This included 472 distinct firms, of which 299 have mentioned a GenAI term at least once (63%). Amongst top adopters in terms of most earnings calls with GenAI terms are companies like Microsoft, Nvidia, ServiceNow, Cognizant Technology Solutions and C.H. Robinson Worldwide.

Table 4.1 shows the descriptive statistics for all the variables used in the empirical analysis in the remaining dataset. As for the dependent variables, firms show an average ROA of 9.27% with substantial variation (Standard Deviation (SD) = 7.65), ranging from -51.50% to 84.5%. TobinsQ also displays variation with a mean of 2.41 and an SD of 2.90 for the market capitalization-total assets share.

The GenAI variables show large sparsity, as expected for the time period. Only around 10% of firm-quarter observations contain at least one GenAI term. The intensity of GenAI-related terms is overall low as well, with a mean of 0.006% mentions of GenAI related terms in a transcript. This sparsity is expected from the literature because of early diffusion of Generative AI.

Dynamic Capabilities indicators show larger representations. Amongst the three dimensions, sensing terms have the greatest appearance on average with a mean of 0.40% of words in a transcript, followed by seizing with 0.247% and transforming with 0.059%. The distributions show presence of DC terminology in calls, although it remains relatively low in frequency, as expected.

The control variables display logical patterns. Where FirmSize is on average 23.91 as the logarithm of firm assets, with modest variation. Firm age ranges from 0 to 143 years, with a mean of 37.44, showing the presence of a mix of mature and younger in the S&P500. Leverage has a mean of 0.32 and CaPex in billions of U.S. Dollars has a mean of 1.84 and a large maximum of 82.99.

The binary knowledge-intensive industry classifier is nicely balanced, as approximately 43% of firms belong to knowledge-intensive category.

Overall, the descriptive statistics show that the cleaned dataset exhibits substantial variation across key variables, enabling a meaningful regression analysis.

Table 4.2: Correlation Matrix of Key Variables

	ROA	TobinsQ	GenAIAdopt	GenAIIntensity	Sensing	Seizing	Transforming	FirmSize	FirmAge	Leverage	CapEx	KnowledgeIndustry
ROA	1.00	0.61	0.07	0.13	0.02	-0.03	-0.01	-0.34	0.02	0.16	-0.06	0.10
TobinsQ	0.61	1.00	0.15	0.22	-0.03	-0.03	0.04	-0.44	-0.06	0.08	-0.08	0.20
GenAIAdopt	0.07	0.15	1.00	0.52	-0.17	0.02	0.09	0.03	-0.04	-0.07	0.10	0.15
GenAIIntensity	0.13	0.22	0.52	1.00	-0.12	0.04	0.08	0.07	-0.04	-0.07	0.23	0.13
Sensing	0.02	-0.03	-0.17	-0.12	1.00	-0.10	-0.09	-0.15	-0.01	0.03	-0.09	-0.06
Seizing	-0.03	-0.03	0.02	0.04	-0.10	1.00	0.03	0.17	0.06	0.01	0.08	-0.02
Transforming	-0.01	0.04	0.09	0.08	-0.09	0.03	1.00	-0.02	-0.01	-0.01	-0.01	0.08
FirmSize	-0.34	-0.44	0.03	0.07	-0.15	0.17	-0.02	1.00	0.12	-0.12	0.47	0.09
FirmAge	0.02	-0.06	-0.04	-0.04	-0.01	0.06	-0.01	0.12	1.00	-0.02	0.03	-0.15
Leverage	0.16	0.08	-0.07	-0.07	0.03	0.01	-0.01	-0.12	-0.02	1.00	-0.20	-0.20
CapEx	-0.06	-0.08	0.10	0.23	-0.09	0.08	-0.01	0.47	0.03	-0.20	1.00	-0.03
KnowledgeIndustry	0.10	0.20	0.15	0.13	-0.06	-0.02	0.08	0.09	-0.15	-0.20	-0.03	1.00

Table 4.2 and figure A.1 show the pairwise correlations among all variables and the correlations heat map, respectively. Overall, the correlations are modest in magnitudes and the highest correlation is 0.61, indicating that there is likely no concern for multicollinearity for the regression analysis.

As expected, the performance indicators have the highest correlation, indicating that accounting and market-based performance indicators tend to move together. However, they both seem to have low associations with the GenAI constructs.

The two GenAI constructs, show an expected positive correlation as one is directly constructed by the other. However, the correlation is modest.

The DC term dimensions show very low correlations, of which the absolute correlations are not larger than 0.10. This shows they are distinct constructs, as expected and explained in theory. The correlation between seizing and transforming is positive

(0.03), whilst those of sensing with seizing (-0.10) or transforming (-0.09) are negative .

The control variables show several patterns. Where firm size is negatively correlated with both performance indicators of ROA (-0.34) and Tobin's Q (-0.44). CapEx correlates strongly with firm size (0.47). This is because firm size is calculated as the logarithm of total assets and both ROA, Tobin's Q and CapEx use that same variable in their construction. Leverage shows a modest positive correlation with ROA (0.16). The asset-intensive industry dummy is positively associated with Tobin's Q (0.20).

Table 4.3: Variance Inflation Factor (VIF) Diagnostics

Variable	**VIF**
GenAIAdopt	1.41
GenAIIntensity	1.45
Sensing	1.07
Seizing	1.04
Transforming	1.02
FirmSize	1.39
FirmAge	1.05
Leverage	1.06
CapEx	1.37
KnowledgeIndustry	1.12

Table 4.3 shows the multicollinearity diagnostics for regression, denoted by Variance Inflation Factors (VIFs), necessary to justify model validity. All VIF values fall well below a commonly accepted threshold of 5. There is no issue for multicollinearity in the dataset, consistent with the low to moderate pairwise correlations observed before.

Distribution plots for all variables are provided in figure A.2, such as violin plots and histograms. They show firms largely differ in scale, asset intensity and investment. These plots show that some variables are largely skewed, such as the performance indicators of ROA and Tobin's Q, but also CapEx. This motivates for additional, appropriate transformations before regressions. Therefore, Tobin's Q and ROA were winsorized at the 1st and 99th percentiles, a standard procedure in accounting and finance research to mitigate the impact of outliers without removing valid observations. The skewness of CapEx shows firms largely differ in investment and was solved for by log transformation, this improves normality, mitigates outliers and keeps interpretability. Other variables contained expected skewness patterns, such as the dictionary-based ones, and were already normalised. Therefore, these variables do not need further transformations and would otherwise lose interpretability. Also, leverage was kept in its ratio form which already has a bounded nature, inappropriate to log transformation. The same holds for the binary variables of GenAI adoption and asset-intensive industry classification. These preprocessing decisions ensured that only variables with measurement distortion or numerical instability were adjusted, whilst keeping the economic properties of the variables in-tact.

4.1.2 Text-Based Variables

Additional descriptive statistics have been constructed for validation checks of the text-based variables as described in Chapter 3 to follow the five validation stages of Short et al. (2010) and to get additional descriptive insights before going into the modeling phase.

	Pre- vs Post-GPT				**Non-Knowledge vs Knowledge Industries**			
Variable	**Pre Mean**	**Post Mean**	**t-stat**	**Sig.**	**Group 0 Mean**	**Group 1 Mean**	**t-stat**	**Sig.**
GenAIAdopt	0.035	0.206	-28.01	***	0.061	0.152	-16.36	***
GenAIIntensity	0.001	0.015	-18.28	***	0.002	0.011	-12.90	***
Sensing	0.450	0.316	45.44	***	0.409	0.387	7.26	***
Seizing	0.237	0.261	-12.07	***	0.248	0.244	2.29	*
Transforming	0.059	0.058	0.24	ns	0.055	0.064	-8.79	***

ns = not significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4: External validity tests comparing dictionary means across temporal (Pre-/Post-GPT) and industry (Knowledge vs Non-Knowledge) contexts.

For external validity, where we try to observe if meaningful similarities or differences are demonstrated between data subsamples, Table 4.4 is provided. They show that, as expected, the average GenAI adoption is significantly higher in the post-GPT period compared to the pre-GPT period and higher in knowledge-intensive industries. Figure 4.1 nicely shows this trend of GenAI terms in earnings call transcripts across year-quarters. These expected and meaningful differences demonstrate that the dictionary successfully captures the underlying construct. The DC dimensions of strategic capabilities are not expected to have large differences between the subsamples. This limited variation is also visible in Table 4.4, which shows slight temporal and industry mean variations, with the temporal variation of transforming as an exception.

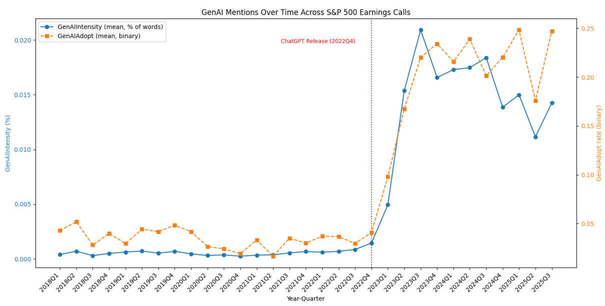

Figure 4.1: GenAI Terms over Time

Table 4.5: Intercorrelations of Dynamic Capabilities Dimensions (N = 12,902).

Dimensions	**Sensing**	**Seizing**	**Transforming**
Sensing	1.00*	-0.10*	-0.09*
Seizing	-0.10*	1.00*	0.03*
Transforming	-0.09*	0.03*	1.00*

Notes. $^{*}p < 0.001$. Pearson correlation coefficients shown.

Dimensionality checks are supported by Table 4.5. This table shows correlations between text-based variables are very low. Indicating that dictionaries constructed are able to capture very distinct constructs. And as discussed in Chapter 2 and 3, sensing, seizing and transforming are seen as conceptually distinct constructs. Therefore, we should not try to explain dynamic capabilities as one variable of impact, as it entails three completely different constructs. Correlations between the binary and intensity adoption variables are present (0.61) but not excessive (> 0.80). However, there are no meaningful incentives to simultaneously model both GenAI variables.

Discriminant validity is shown in figure A.1. This confirms there are indeed low associations between the constructed variables and other distinct variables.

Measuring predictive validity is done in the next part, where we test whether the dictionary scores predict theoretically relevant outcomes in the expected direction.

4.2 Main Results

	Model 1a – ROA (Adoption)	Model 1b – ROA (Intensity)
GenAIAdopt	0.422+	–
	(0.241)	
FirmSize	-2.817***	-2.880***
	(0.688)	(0.688)
Leverage	-1.680	-1.664
	(2.116)	(2.111)
CapEx	0.143	0.142
	(0.276)	(0.276)
GenAIIntensity	–	6.819**
		(2.344)
Num. Obs.	12901	12901
R^2	0.789	0.789
R^2 Within	0.032	0.034
RMSE	3.18	3.17
Std. Errors	by: RIC	by: RIC

ns = not significant (no marker), + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.6: Baseline regression results for ROA with GenAI adoption and intensity.

Table 4.6 shows the results of the first firm and year-quarter fixed-effect regressions. Model 1a shows that the binary GenAI adoption variable has a marginally significant positive association with ROA ($\beta = 0.42$, p < 0.10), whilst the GenAI adoption intensity variable in model 1b shows an even stronger and statistically more significant positive association with ROA ($\beta = 6.819$, p < 0.01). Firm size is consistently negatively associated with ROA and highly significant across both models ($\beta = -2.817$ and $\beta = -2.880$, p < 0.001). Other control variables such as leverage and CapEx show insignificant relationships with ROA. The model fit statistics indicate similar overall explanatory power ($R^2 = 0.789$ and Within $R^2 = 0.032$ and 0.034). Standard errors have been clustered at the company level to account for serial correlation and heteroskedasticity within firms across time. Firm age was dropped because of collinearity with the fixed effects.

	Model 2A – ROA (Adopt × DC)	**Model 2B – ROA (Intensity × DC)**
GenAIAdopt	0.195	–
	(0.255)	
Sensing	-0.240	-0.437
	(0.509)	(0.517)
Seizing	0.081	-0.015
	(0.530)	(0.512)
Transforming	-4.283***	-4.005***
	(0.974)	(0.967)
GenAIAdopt × Sensing	-2.821*	–
	(1.233)	
GenAIAdopt × Seizing	-0.590	–
	(1.676)	
GenAIAdopt × Transforming	2.735	–
	(2.336)	
GenAIIntensity	–	6.659*
		(3.268)
GenAIIntensity × Sensing	–	-2.501
		(13.728)
GenAIIntensity × Seizing	–	1.263
		(20.282)
GenAIIntensity × Transforming	–	-6.127
		(13.068)
FirmSize	-2.853***	-2.873***
	(0.685)	(0.687)
Leverage	-1.532	-1.523
	(2.103)	(2.104)
CapEx	0.179	0.148
	(0.277)	(0.277)
Num. Obs.	12901	12901
R^2	0.790	0.790
R^2 Within	0.037	0.037
RMSE	3.17	3.17
Std. Errors	by: RIC	by: RIC

ns = not significant (no marker), + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.7: Regression results for ROA with GenAI adoption/intensity and dynamic capability interactions.

Table 4.7 shows the results of the second fixed-effects regression which includes the dynamic capabilities dimensions as interaction terms. Results of model 2a show that the main effect of binary GenAI adoption on ROA is not significant any more. From the DC dimensions, transforming shows a significantly strong negative effect on ROA across both models ($\beta = -4.283$ and $\beta = -4.005$, p < 0.001), the others are insignificant. The association of the interaction of binary GenAI adoption and sensing is statistically negative with ROA ($\beta = -2.821$, p < 0.05). Whilst the other interactions of seizing and transforming are insignificant. In model 2b, which uses GenAI adoption intensity, there are no statistically significant interaction terms. However, the association of GenAI adoption intensity with ROA itself remains positive and significant to some extent ($\beta = 6.659$, $p < 0.05$). Across both models, again, firm size remains consistently negative and significantly associated with ROA ($\beta = -2.853$ and $\beta = -2.873$, $p < 0.001$). The model fit statistics indicate similar overall explanatory power ($R^2 = 0.790$ and Within $R^2 = 0.037$). Compared to model 1a, the GenAI adoption coefficient in 2a loses some significance but remains similar in positive sign and magnitude. Compared to model 1b, the GenAI intensity coefficient in model 2b remains similar in sign and magnitude, losing a bit of significance too but remaining significant.

	Model 3A – ROA (Adopt × Industry)	**Model 3B – ROA (Intensity × Industry)**
GenAIAdopt	0.710*	–
	(0.307)	
GenAIIntensity	–	10.879*
		(5.535)
GenAIAdopt × KnowledgeIndustry	-0.485	–
	(0.495)	
GenAIIntensity × KnowledgeIndustry	–	-4.878
		(6.212)
FirmSize	-2.791***	-2.869***
	(0.687)	(0.687)
Leverage	-1.689	-1.669
	(2.115)	(2.111)
CapEx	0.133	0.137
	(0.277)	(0.277)
Num. Obs.	12901	12901
R^2	0.789	0.789
R^2 Within	0.032	0.034
RMSE	3.18	3.17
Std. Errors	by: RIC	by: RIC
ns = not significant (no marker), + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

Table 4.8: Regression results for ROA with GenAI adoption/intensity and industry interactions.

Table 4.8 shows the third regression results, which includes interaction terms of GenAI variables with the asset-intensive industry variable. The terms of binary and intensity GenAI adoption are still positively and significantly associated with ROA in both models ($\beta = 0.710$ and $\beta = 10.879$ respectively, $p < 0.05$), with slightly larger coefficients. The interaction term with knowledge industry is not statistically significant in both models. Across both models, firm size remains negative and highly significant ($\beta =$ -2.791 and $\beta =$ -2.869 respectively, $p < 0.001$). The model fit statistics indicate somewhat similar overall explanatory power across both models ($R^2 = 0.789$ and Within $R^2 = 0.032$ and 0.034).

4.3 Robustness Checks

Alterations to the regression have been made to check for model robustness. This includes swapping the performance indicator of ROA for Tobin's Q (shown in Table A.2). And to additionally regress on a sub-sample of the data which includes only the post-GPT data (shown in Table A.3 and Table A.4), as for this data, GenAI adoption scores are more represented. This resulted in summary Table 4.9 which shows for every hypotheses, the corresponding variable that tests it, their effects and significance. For the full sample, the interaction term of binary GenAI adoption and the sensing capability also has a negative effect on Tobin's Q, but with slightly weaker effect and significance (β = -0.539, p < 0.10). The post-GPT subsample however shows additional significant effects. The interaction effect of sensing with both the binary and intensity GenAI adoption variables are stronger negative and significant (β = -3.558 and β = -18.000, with p < 0.01). Again, these effects on Tobin's Q are also present but weaker in effect and significance (β = -0.955 and β = -7.220, with p < 0.01 and p < 0.05 respectively). Additionally, in the post-GPT stage, the association of the interaction term between binary GenAI adoption and asset-intensive industries with ROA is positive and significant (β = 0.733, p < 0.01). The significant effects of the baseline model of the binary and intensity adoption variables of GenAI on ROA have lost their significance in the post-GPT subsample.

Hypothesis	Variable	Full Sample (2018–2025)				Post-GPT (2023–2025)			
		ROA	Sig.	TobinQ	Sig.	ROA	Sig.	TobinQ	Sig.
H1a	GenAIAdopt	0.422	+	0.074	ns	0.113	ns	0.013	ns
H1b	GenAIIntensity	6.819	**	1.108	ns	0.824	ns	0.030	ns
H2a	Sensing × GenAIAdopt	-2.821	*	-0.539	+	-3.558	**	-0.955	**
H2a (alt)	Sensing × GenAIIntensity	-2.501	ns	1.051	ns	-18.000	**	-7.220	*
H2b	Seizing × GenAIAdopt	-0.590	ns	-0.683	ns	-0.714	ns	-0.091	ns
H2b (alt)	Seizing × GenAIIntensity	1.263	ns	-4.486	ns	6.146	ns	3.789	ns
H2c	Transforming × GenAIAdopt	2.735	ns	-0.207	ns	-0.511	ns	-0.128	ns
H2c (alt)	Transforming × GenAIIntensity	-6.127	ns	-2.456	ns	-2.203	ns	1.230	ns
H3a	GenAIAdopt × KnowledgeIndustry	-0.485	ns	-0.016	ns	0.733	**	0.050	ns
H3a (alt)	GenAIIntensity × KnowledgeIndustry	-4.878	ns	1.262	ns	1.030	ns	-1.018	ns

ns = not significant, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.9: Comparison of regression coefficients and significance levels for all hypotheses across the full sample and the post-GPT subsample.

Discussion

The credibility of the main results is supported by the consistency of the results across multiple model specifications and the two different operationalizations of GenAI adoption. In particular, the distinction between the two operationalizations in strength remain qualitatively similar when accounting for DC theory interactions and industry heterogeneity. The robustness of the empirical findings is further supported by alternative model specifications. Using Tobin's Q as a market-based performance measure yields weaker but non-contradictory results. This is conceptually expected as market valuations incorporate forward-looking expectations which are not immediately reflected in this model. Estimations on the post-GPT subsample show reduced precision, reflecting the minimised data window, whilst still preserving the qualitative patterns observed in the full sample. Across models, R^2 values remain high due to inclusion of firm and year-quarter fixed effects which capture firm-specific heterogeneity and common time-varying shocks. Which explains the modest within R^2 values too, as most variation of within a firm is captured by these effects and other variables are slow-moving constructs. The stability of RMSE across model specifications indicates that inclusion of variables does not negatively affect the model. Together, these diagnostics support internal validity and robustness of empirical findings which can now be discussed.

5.1 Interpretation

Results of the main model show that GenAI adoption is positively associated with operating performance (ROA) to some extent, although the evidence marginally significant. This suggests the binary term of adoption alone may be insufficient to generate immediate performance effects. This pattern relates back to theory with the idea that new technologies do not automatically associate with performance gains upon first adoption, as they need to be integrated into complex existing company structures and processes (Coccia, 2024; Sánchez et al., 2025). And relating back to RBV theory, mere mentioning of the technology does not immediately associate with performance benefits, as performance improvements typically require real integration of the technology, complementing with existing workflows (Kane et al., 2015; Singh et al., 2024; Wamba-Taguimdje et al., 2020). However, there is a positive association present, which is consistent with GenAI research streams that have promising forward-looking views on the capabilities of the technology and its implications for business (Fui-Hoon Nah et al., 2023; Mondal et al., 2023; Rana et al., 2024; Sedkaoui & Benaichouba, 2024). This extends previously discussed literature that have found similar results on the GenAI-performance relationship (Cui, 2025; European Central Bank., 2025; Jia et al., 2024). Opposed to ROA, results show no significant relationship of binary GenAI adoption with Tobin's Q. This suggests that markets may not systematically price GenAI adoption disclosures. Potentially due to the ambiguity of adoption announcements. This provides nuance to previously discussed literature applying Tobin's Q (Cui, 2025; Mbanyele, 2025).Also, in the post-GPT stage, effects are absent which may reflect the shorter time window, including fewer within-firm variations of the variable or that performance gains from adoption require time to materialize. However, although not significantly present in the extended models for robustness, `H1a` can be confirmed to some extent.

In contrast to binary GenAI adoption, GenAI adoption intensity exhibits a stronger and statistically more significant association with ROA in the main results. This indicates that within-firm more intensive GenAI adoption compared to prior situations, has a positive association with firm performance measured by ROA. This is consistent with the idea that deeper engagement with the technology captures meaningful integration of it for business. This aligns with previously stated theory that performance benefits are more likely to exist when firms engage more with the technology, therefore reaching effective utilization rather than mere mentioning (Kane et al., 2015; Sedkaoui & Benaichouba, 2024). As value is expected to come when the technology is embedded into processes to become valuable. This finding is consistent with the examined GenAI adoption literature that have found similar positive associations between its adoption and performance, measured by intensity (European Central Bank., 2025; Jia et al., 2024; Mbanyele, 2025). However, it is important to state that the effect does not apply to Tobin's Q and is not captured in the post-GPT subsample either. This can be interpreted as before, that GenAI adoption intensity is not reflected in the forward-looking expectations of firm value; at least for the investigated time horizon. Again, the post-GPT stage might have unclear within-firm variations for the limited time period. Still, `H1b` is supported for ROA in the full sample, but the evidence is not robust across Tobin's Q or the post-GPT subsample.

Results of the model including theoretical dimensions of dynamic capabilities show mixed and context-dependent results regarding the moderating role of sensing capabilities of the firm. In the full sample, the within-firm increase in sensing capabilities negatively and significantly impacts the association between GenAI adoption and firm performance.

These findings suggest that higher sensing capabilities do not consistently strengthen the positive association between GenAI and firm performance. From DC theory, although sensing capabilities have said to be essential for identifying technological opportunities (Teece, 2018; Teece et al., 1997), they have contradictory effects. This indicates that DC capabilities drive performance gains through different routes as explained by Wilden et al. (2013), Bughin (2024) and Protogerou et al. (2012). And that potentially, GenAI can be framed as a dynamic capability by itself, not linked to the existing capability of sensing (Cui, 2025; Wamba-Taguimdje et al., 2020) The negative association could indicate that the sensing phase includes trial and error, organizational disruption or delayed payoffs of GenAI technology adoption (Coccia, 2024; Sánchez et al., 2025). Results suggest that firms growing their sensing capabilities show weaker performance gains from GenAI. Again, we see this effect to be weaker on Tobin's Q, which suggests that the forward-looking expectations of firm value are weakened less heavily. The associations between GenAI adoption and performance are even stronger weakened by greater sensing capabilities in the post-GPT subsample, also including adoption intensity now. This suggests that increased sensing weakens the associations of GenAI with performance, especially when intensively engaged with the technology. This again relates to theory that if we view sensing of GenAI as an early stage of adoption, that large firms may struggle with its successful adoption which relates to costs (Chui, Hazan, et al., 2023; Sánchez et al., 2025). The contradictory results indicate that we cannot support `H2a`.

The results provide no empirical support for the moderating role of seizing and transforming capabilities across all specifications, that is, statistical insignificance for both ROA and Tobin's Q and in both the full sample and the post-GPT subsample. Relating back to theory, seizing capabilities entail resource mobilization, investment decisions and the commitment to specific strategies. And transforming capabilities entail reconfiguration of the business and business and process adjustments (Teece, 2018; Teece et al., 1997). Whilst theory states that these are important to translate technological opportunities into firm value, the results show no proof of this. Again, this could indicate that GenAI relates to performance via a different channel than through dynamic capabilities. Or that interaction with GenAI is a dynamic capability in itself (Cui, 2025; Wamba-Taguimdje et al., 2020). Alternatively, seizing and transforming capabilities are slow-moving constructs. So, increase in seizing or transforming capabilities within a firm might not immediately strengthen the positive GenAI adoption and performance association. Instead, the transforming capability shows to have a significantly negative association with both ROA and Tobin's Q in both the full and post-GPT subsample. This relates to theory that organizational restructuring is costly and has negative associations with both accounting and forward-looking performance (Teece et al., 1997; Wilden et al., 2013). Overall, both `H2b` and `H2c` are not supported.

Results for the full sample show that the interaction between GenAI adoption and knowledge-intensive industries is insignificant. However, when solely focusing on GenAI adoption in the post-GPT stage, the associations is present. This suggests that firms in knowledge-intensive industries strengthen the association between GenAI adoption and ROA in the post-GPT subsample. From a theoretical perspective, this pattern is consistent with statement that the technology of GenAI may benefit knowledge-intensive industries more, given their greater reliance on information processing, analytical tasks and knowledge-based workflows (Bughin, 2024; Wael AL-khatib, 2023). This complements existing research that showed similar positive results for knowledge-intensive industries (Eisfeldt et al., 2023; European Central Bank., 2025; Huang & Lin, 2025; Jia et al., 2024; Mbanyele, 2025; Reddy et al., 2025). The insignificance of the other results might relate to theory that frames GenAI as a general-purpose technology, affecting all, not limited to knowledge-intensive industries (Sharma et al., 2024). Although not completely robust, `H3a` receives partial support in a context-dependent environment.

5.2 Implications for Theory and Practice

Results in this thesis contribute to the emerging literature on generative AI by empirically demonstrating the importance of distinguishing between GenAI adoption and GenAI adoption intensity. Where results have shown that mere mentioning of GenAI and acknowledgement of its existence only shows moderate associations with firm performance, whereas thorough discussion of the technology shows strong associations. This finding strengthens theoretical arguments that financial business value creation depends on the depth of GenAI adoption. Furthermore, findings add to generative AI and business literature that knowledge-intensive industries seem to benefit more from its adoption than other industries. Additionally, it contributes to dynamic capabilities by adding nuance to the role of DC dimensions in the context of the emerging GenAI technology. On the contrary to theoretical expectations, results indicate that within-firm changes in sensing, seizing and transforming capabilities do not systematically strengthen the GenAI-performance relationship. This suggests that they may have associations in the longer-term, that the relationship of GenAI with performance is captured through another indirect relationship, not immediately reflected by DC in direct accounting outcomes. Or more interestingly, that the capability of a firm to adopt GenAI is a DC in itself. Although not all significant, the results provide proof to measure DC dimensions through text-based constructs.

As for strategic managers and investors, results imply that the technology of GenAI has promising associations with firm performance. Results motivate firms to intensively engage with the technology and not merely acknowledge its presence. These results could drive investment decisions, mainly, but not limited to, firms in knowledge-intensive industries. Findings related to sensing capabilities suggest that exploratory activities around the technology come at a price for performance in the short-term. Managers should anticipate these costs of experimentation with the technology.

5.3 Limitations and Future Work

One of the main limitations anchors itself in the measurement of text-based constructs. Where constructs of GenAI adoption, both binary and intensity, and the DC dimensions are constructed using text-based measures. Whilst this approach has the benefit of scalability, it may not fully capture the actual theoretical construct. Term mentioning in a corporate disclosure does not mean real implementation of GenAI in business processes or real capabilities of a firm to sense, seize and transform. Firms may differ in how transparently they disclose GenAI related activities and strategic signalling cannot be easily distinguished from real usage of GenAI in operations. Therefore, measures observed in this thesis should be interpreted as proxies for GenAI engagement rather than direct observations of technology deployment. Therefore, as for future work, our dictionary-based, bag-of-words methodology can be extended with other methodologies such as getting labour-based scores or scores generated using llm's to better capture actual meaning of text on a large-scale instead of mere mentioning. Or complement text-based measures with survey-based measure or case studies. Llm's could also assist in capturing GenAI use cases in text disclosures. This broadens the research to additionally investigate for which GenAI use cases performance gains are highest and in which industries.

Secondly, limited validation and robustness checks have been done on the creation of the text-based measures. As explained before, content validity checks could have been performed by comparing the created word list with other already existing word lists or by using experts to review the list and work with inter rater agreement scores. Apart from manual, personal interpretation, none of the above have been done. Also, no manual checks have been done on the scoring of a subsample of transcripts. This limits the validity of the created constructs. Also, external validity could have been extended by getting scores for the constructs based on other corporate disclosure data such as annual reports and compare them with current scores to see if they are generalizable. Additionally, the scope could be enlarged to also cover companies outside of the U.S. to get a full picture of the diffusion of the technology of GenAI throughout the world and see where it is best able to support business.

Thirdly, the research is limited due to only using firm fixed effect regressions. This entails that all relationships identified are within-firm variation over time. Whilst controlling for firm and year effects strengthens internal validity by mitigating unobserved heterogeneity, it may potentially weaken the effects of slowly evolving constructs such as the dynamic capabilities. So, rather than real absence of theoretical constructs they are limitedly shown because of the method for analysis. Also, the analysis remains observational and cannot establish causal relationships. This means findings are interpreted as systematic correlations instead of causal effects. Therefore, as for future work, different analyses can be performed. Such as Difference in Difference (DiD) approaches to measure pre- and post-GPT dynamics; or instrumental variable (IV) analysis, to strengthen causal inference.

Fourth, the study focuses on direct (short-term) accounting-based performance (ROA) and market-based valuation (Tobin's Q). These measures may not fully capture longer-term strategic benefits of GenAI adoption or dynamic capabilities. For future research, lagged effects could be modelled to better capture temporal dynamics through which GenAI adoption influences firm-performance and which could examine whether dynamic capabilities have delayed performance benefits. For example by dynamic panel models, with lagged variables. Also, the performance indicator set could be expanded to get a more comprehensive understanding of the value generated by GenAI, such as innovation measures or productivity measures.

Despite these limitations, this study has provided a systematic and theoretically-informed examination of the association of GenAI adoption with company performance, offering a foundation for future research on the impact of Generative AI for business.

Conclusion

The goal of this thesis was to fill the gap in academic literature that falls behind on the rapid advancements of the technology of Generative AI. More specifically, it aimed to investigate the relationship between Generative AI adoption and company performance, and how Dynamic Capabilities theory and industry context condition this relationship; in order to better understand how performance gains arise from the technology implementation. This aims to inform strategic managers and investors about potential returns when implementing GenAI, to help mitigate the insecurity of financial returns related to GenAI technology adoption.

This research objective was addressed by using a panel data approach with firm and year-quarter fixed-effects regressions. In this panel data, GenAI adoption and Dynamic Capabilities theory dimensions variables were constructed using a bag-of-words, text-based analysis of corporate disclosures of the S&P500 firms for the period of 2018 to 2025. Firm performance was captured using both accounting-based (ROA) and market-based (Tobin's Q) indicators. By incorporating interaction terms with DC dimensions and knowledge-intensive industry context, the analysis investigated not only whether GenAI is associated with firm performance but also under which organizational capabilities and textual conditions the association varies.

The empirical results show several key findings. First, binary GenAI adoption shows positive but weak associations with firm performance, whereas GenAI adoption intensity shows stronger and more robust associations with performance in the main results. This highlights that deeper interaction with GenAI is more closely related to performance gains than mere mentioning of the term. Secondly, the analysis provided limited support for the moderating role of dynamic capabilities in the GenAI-performance relationship. The sensing capability has shown contradictory results to what was expected, by weakening the GenAI-performance relationship. Overall, sensing, seizing and transforming capabilities do not consistently strengthen the short-term association, suggesting that they may have positive influence through the longer-term, or that they influence performance through more complex, indirect mechanisms. Thirdly, a knowledge-intensive industry context plays a positive role on the GenAI-performance relationship with mixed support, only showing evidence in the post-GPT subsample whilst not robust across the full sample or different performance measures.

Together, these findings contribute to the literature on generative AI and business, emphasizing the potential performance gains associated with GenAI adoption. And it extends by applying industry contexts to the relationship, showing results in line with previous literature with limited support. It provides nuance on dynamic capabilities theory literature for the technology of GenAI by suggesting that performance benefits from GenAI may not immediately materialize through DC theory or that measurement of the constructs through text-based analysis of corporate disclosures is limited. From a practical perspective, these findings can drive for investment decisions in GenAI adoption to benefit from its promising potential, as findings help to reduce the uncertainty of financial returns as a barrier to adoption. Although slightly greater performance can be expected in knowledge-intensive industries, weakened results show benefits from GenAI are not limited to industry-contexts, framing GenAI as a potential general-purpose technology. Additionally, firms engaging in exploratory sensing activities in the rapid technologically changing environment of GenAI should anticipate short-term weakened performance gains.

To conclude, this thesis demonstrates the ability to capture theoretical constructs from text-based corporate disclosures. But more importantly, that adoption of the technology of GenAI positively relates to company performance in the S&P500 context. And that larger gains are expected when more intensively engaging with the technology rather than mere adoption, and in knowledge-intensive industries. How GenAI relates with firm performance through dynamic capabilities theory remains unclear in this thesis, whilst framing interaction with GenAI as a distinct dynamic capability in itself gives an interesting take-away for future research. As the technology will continue to rapidly evolve and diffuse across business, future research is well-positioned to build on this methodology and findings to be better able to capture the complex dynamics of how GenAI relates to company performance. This thesis leaves room for future research in text- and regression analysis methods and scope, by examining longer-term, lagged effects and causal mechanisms through which GenAI influences organizational performances; and by applying llm's and validation methods to better capture text-based constructs which are scalable across larger time, firm and industry contexts.

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Additional Tables and Figures

Table A.1: Text-based Variable Dictionaries

Construct	Dictionary Terms
Sensing Capability	scan, scanning, search, searching, explore, exploring; monitor, monitoring, sense, sensing; identify, identifying, detect, detecting; anticipate, anticipating, observe, observing; evaluate, evaluating, assess, assessing; track, tracking; market intelligence, competitive intelligence; customer needs, customer insights; environmental scanning; trend identification, trend spotting; pattern recognition; technology scouting; opportunity identification; emerging technologies; gather external knowledge; best practices; discover, research, scout, read, recognize; trends, forecast, indicators.
Seizing Capability	invest, investing, investment; commit, committing, commitment; allocate, allocating, resource allocation; mobilize, mobilizing; capture value; commercialize, commercializing, commercialization; evaluate, evaluating, assess alternatives; decide, decision making; prioritize opportunities; seize opportunities; business model design, design business model; launch initiative, launch project; implement, implementing; adopt; exploit opportunities; initiate project, initiate initiative; capture, innovation, apply, start; deploy, acquire, select, choose.
Transforming Capability	reconfigure, reconfiguring, reconfiguration; restructure, restructuring; redeploy, redeployment; recombine, recombining; realign, realigning; renew, renewal; adapt, adapting, adaptation; transform, transforming, transformation; modify, modifying; upgrade, upgrading; orchestrate, orchestrating; integrate, integration; reengineer, reengineering; redesign, process redesign, workflow redesign; continuous improvement; update processes; reallocate resources; discontinue practices; organizational redesign; organizational change; resource reconfiguration; adjust, replacement, reconstitute.

Continued on next page

Table A.1: Text-based Variable Dictionaries (continued)

Construct	Dictionary Terms
GenAI Core Terms	generative ai, gen ai, genai; large language model, large-language model, llm; foundation model, foundational model; chatgpt, gpt, gpt-3, gpt3, gpt-4, gpt4, gpt-4o; openai, anthropic, claude; google gemini, gemini model; meta llama, llama 2, llama 3; azure openai; microsoft copilot, github copilot, ai copilot; ai assistant(s); ai agent(s); generative ai models; generative ai technology; generative ai applications.
GenAI Strategy Terms	genai strategy, genai roadmap; genai adoption, genai implementation; genai initiative(s); genai capability, genai capabilities; genai infrastructure; genai platform(s); genai investment(s); genai deployment; genai solution(s); llm deployment, llm integration; foundation model deployment, foundation model integration; llm-enabled, llm powered, llm-powered; genai powered, genai-enabled.
GenAI Use-Case Terms	text generation, content generation, code generation; document processing, document understanding; semantic search, intelligent search; knowledge assistant, search assistant; chatbot, virtual assistant, ai chatbot; customer service bot, call center automation; workflow automation, process automation; automated decision(s); recommendation system, recommender system; synthetic data; fine-tuning, fine tuning; model inference; natural language interface, natural language query/queries.

	1a Adoption	**1b** Intensity	**2A** Adopt × DC	**3A** Adopt × Industry
GenAIAdopt	0.074	–	0.044	0.083
	(0.073)		(0.068)	(0.065)
GenAIIntensity	–	1.108	–	–
		(1.039)		
Sensing_c	–	–	-0.198	–
			(0.144)	
Seizing_c	–	–	0.351*	–
			(0.167)	
Transforming_c	–	–	-0.572*	–
			(0.290)	
GenAIAdopt × Sensing_c	–	–	-0.539+	–
			(0.326)	
GenAIAdopt × Seizing_c	–	–	-0.683	–
			(0.493)	
GenAIAdopt × Transforming_c	–	–	-0.207	–
			(0.808)	
GenAIAdopt × KnowledgeIndustry	–	–	–	-0.016
				(0.137)
FirmSize	-1.803***	-1.813***	-1.813***	-1.803***
	(0.203)	(0.201)	(0.203)	(0.202)
Leverage	0.182	0.185	0.195	0.182
	(0.665)	(0.665)	(0.664)	(0.665)
CapEx	0.185*	0.184*	0.190*	0.184*
	(0.085)	(0.086)	(0.085)	(0.085)
Num. Obs.	12901	12901	12901	12901
R^2	0.869	0.869	0.869	0.869
R^2 Within	0.139	0.140	0.142	0.139
RMSE	0.90	0.90	0.90	0.90
Std. Errors	by: RIC	by: RIC	by: RIC	by: RIC

ns = not significant, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Fixed-effects regression results for Tobin's Q (Full sample, 2018–2025).

	1a2 Adopt	**1b2** Int	**2A2** Adopt×DC	**2B2** Int×DC	**3A2** Adopt×Ind	**3B2** Int×Ind
GenAIAdopt	0.113	–	0.057	–	-0.291*	–
	(0.147)		(0.140)		(0.147)	
GenAIIntensity	–	0.824	–	-0.104	–	-0.049
		(1.080)		(1.328)		(1.750)
Sensing_c	–	–	0.168	-0.463	–	–
			(0.532)	(0.561)		
Seizing_c	–	–	0.094	-0.044	–	–
			(0.558)	(0.570)		
Transforming_c	–	–	-3.847***	-3.897***	–	–
			(0.950)	(1.009)		
GenAIAdopt × Sensing_c	–	–	-3.558**	–	–	–
			(1.087)			
GenAIAdopt × Seizing_c	–	–	-0.714	–	–	–
			(1.002)			
GenAIAdopt × Transforming_c	–	–	-0.511	–	–	–
			(1.833)			
GenAIIntensity_c× Sensing_c	–	–	–	-18.000**	–	–
				(6.610)		
GenAIIntensity_c× Seizing_c	–	–	–	6.146	–	–
				(7.123)		
GenAIIntensity_c× Transforming_c	–	–	–	-2.203	–	–
				(10.545)		
GenAIAdopt × KnowledgeIndustry	–	–	–	–	0.733**	–
					(0.281)	
GenAIIntensity × KnowledgeIndustry	–	–	–	–	–	1.030
						(2.111)
FirmSize	-2.363***	-2.352***	-2.458***	-2.376***	-2.344***	-2.349***
	(0.615)	(0.618)	(0.627)	(0.622)	(0.613)	(0.618)
Leverage	-2.731	-2.749	-2.754	-2.665	-2.735	-2.753
	(1.983)	(1.986)	(2.004)	(1.994)	(1.979)	(1.985)
CapEx	-0.379	-0.379	-0.327	-0.367	-0.381	-0.379
	(0.375)	(0.376)	(0.372)	(0.374)	(0.375)	(0.376)
Num. Obs.	4889	4889	4889	4889	4889	4889
R^2	0.913	0.913	0.914	0.914	0.913	0.913
R^2 Within	0.018	0.018	0.035	0.027	0.021	0.018
RMSE	1.98	1.98	1.96	1.97	1.97	1.98
Std. Errors	by: RIC	by: RIC	by: RIC	by: RIC	by: RIC	by: RIC

ns = not significant, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Fixed-effects regression results for ROA (Post-GPT subsample).

	1a2 Adopt	1b2 Int	2A2 Adopt×DC	2B2 Int×DC	3A2 Adopt×Ind	3B2 Int×Ind
GenAIAdopt	0.013	–	-0.001	–	-0.014	–
	(0.055)		(0.052)		(0.049)	
GenAIIntensity	–	0.030	–	-0.505	–	0.893
		(0.574)		(0.693)		(0.847)
Sensing_c	–	–	-0.160	-0.351*	–	–
			(0.133)	(0.139)		
Seizing_c	–	–	0.109	0.097	–	–
			(0.161)	(0.187)		
Transforming_c	–	–	-1.227***	-1.258***	–	–
			(0.322)	(0.293)		
GenAIAdopt × Sensing_c	–	–	-0.955**	–	–	–
			(0.326)			
GenAIAdopt × Seizing_c	–	–	-0.091	–	–	–
			(0.404)			
GenAIAdopt × Transforming_c	–	–	-0.128	–	–	–
			(0.694)			
GenAIIntensity_c× Sensing_c	–	–	–	-7.220*	–	–
				(3.582)		
GenAIIntensity_c× Seizing_c	–	–	–	3.789	–	–
				(4.761)		
GenAIIntensity_c× Transforming_c	–	–	–	1.230	–	–
				(4.234)		
GenAIAdopt × KnowledgeIndustry	–	–	–	–	0.050	–
					(0.104)	
GenAIIntensity × KnowledgeIndustry	–	–	–	–	–	-1.018
						(1.053)
FirmSize	-1.889***	-1.889***	-1.917***	-1.907***	-1.888***	-1.892***
	(0.360)	(0.361)	(0.364)	(0.364)	(0.360)	(0.361)
Leverage	-0.943	-0.944	-0.941	-0.911	-0.944	-0.940
	(0.842)	(0.841)	(0.841)	(0.838)	(0.842)	(0.841)
CapEx	0.069	0.069	0.085	0.074	0.069	0.069
	(0.116)	(0.116)	(0.116)	(0.117)	(0.116)	(0.116)
Num. Obs.	4889	4889	4889	4889	4889	4889
R^2	0.930	0.930	0.931	0.931	0.930	0.930
R^2 Within	0.076	0.075	0.088	0.086	0.076	0.076
RMSE	0.65	0.65	0.65	0.65	0.65	0.65
Std. Errors	by: RIC	by: RIC	by: RIC	by: RIC	by: RIC	by: RIC

ns = not significant, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Fixed-effects regression results for Tobin's Q (Post-GPT subsample).

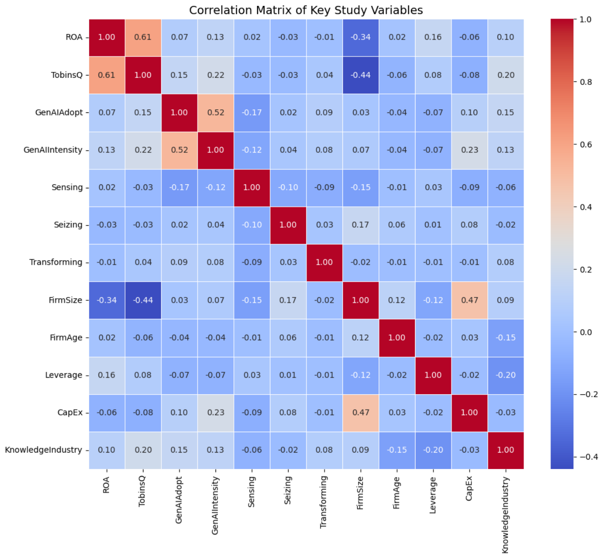

Figure A.1: Correlation Heatmap

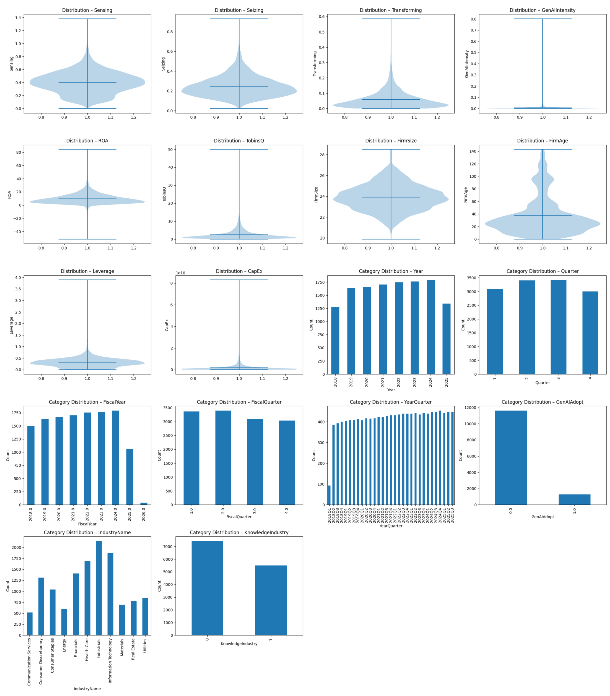

Figure A.2: Distribution Plots