ARTIFICIAL INTELLIGENCE NARRATIVES IN EARNINGS CALLS AND THEIR EFFECT ON MARKET DYNAMICS: A STUDY OF VOLUME AND VOLATILITY IN LEADING TECH STOCKS

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ABSTRACT

ARTIFICIAL INTELLIGENCE NARRATIVES IN EARNINGS CALLS AND THEIR EFFECT ON MARKET DYNAMICS: A STUDY OF VOLUME AND VOLATILITY IN LEADING TECH STOCKS

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The thesis titled *"Artificial Intelligence Narratives in Earnings Calls and Their Effect on Market Dynamics: A Study of Volume and Volatility in Leading Tech Stocks,"* explores the short term financial impact of AI related corporate narratives presented during the quarterly earnings calls by the five leading NASDAQ listed technology companies (Google, Microsoft, Meta, Apple and Nvidia). Earning calls have become a tactical means to influence the expectations of investors using a purposefully crafted language as artificial intelligence has taken stage. This research centers on the impact of specific AI themed narratives ranging from optimism and uncertainty to investment and ethical risk on immediate market behavior, specifically, the fluctuations in trading volume and volatility.

The motivation behind this research comes from the recent recognition that qualitative disclosures now weigh equally, if not more compared to the traditional financial metrics in shaping the investor sentiment. Quantitative metrics such as earnings per share and financial ratios do remain core components of financial analysis. But the language used by executives -

especially concerning emerging technologies like AI – can often serve as a signal of strategic intent, competitive positioning, and anticipated risks the business is surrounded by. Yet, existing financial analysis tools such as including sentiment lexicons, AI generated summaries, and predefined models, do not have the thematic specificity and transparency needed to capture the evolving vocabulary and contextual subtleties of AI related communication.

To fill this gap, the research suggests a systematic methodology that involves building a custom AI lexicon, thematically analyzing earnings call transcripts, and empirically connecting these narrative categories to short term market indicators. It uses text mining, winsorization, and regression analysis to evaluate the extent to which AI narratives correlate with abnormal trading activity and volatility changes in the short term. This includes metrics such as the VIX or VXN. The study also provides a replicable and interpretable approach to narrative finance by comparing custom lexicon to generic sentiment model.

This research interlinks multiple disciplines of financial verbiage, AI communication and movements in the financial market. The study focuses on some practical insights of analyzing the impact of AI narratives through the dissection of the language used on earnings calls which would help the investors interpret the cues into trading strategies. This research addresses a new gap in the literature and equips the financial wizards to better assess and respond to the narratives around Artificial Intelligence in the financial aspect.

Keywords: AI Narratives, Earnings Calls, Financial Linguistics, Market Dynamics, Custom Lexicon, NLP

CHAPTER 1

INTRODUCTION

In the last decade, artificial intelligence (AI) has evolved from a sub discipline of technical computer science to an influential force that determines corporate strategy, distributes capital, and defines competitive positioning in the global economy. The change is most noticeable in the sphere of technology, as companies progressively base their expansion stories on the developments in the machine learning, large language models, and automated systems that run on data. Since the release of the publicly accessible generative AI systems at the end of 2022 (Cupać, Schopmans and Tuncer-Ebetürk, 2024), corporate disclosures have taken a distinct turn: no longer seen as a side research project, AI has become a core driver of revenue, productivity, and dominance in the market in the long term by the companies (Gao *et al.*, 2023).

Quarterly earnings calls have a unique place in the corporate communication system (Holzman, Miller and Twedt, 2023). Contrasting with statutory filings, which are limited to inflexible reporting frameworks, the earnings calls provide the top management with a chance to express the strategic intent in situational contexts, address the analyst questions, and package the corporate performance in the ways that combine factual reporting with the futuristic interpretation (Ugras and Ritter, 2025). As a result, such calls are not informational occasions but performative discourses where companies are directly involved in creating the perception of investors regarding their technological direction, competitive risks and subsequent growth opportunities (Naeem *et al.*, 2021).

In this regard, AI has become a very powerful narrative tool (Chubb, Reed and Cowling, 2022). The pronouncements about Microsoft being infused with AI in all strata of the technology stack, or about Alphabet being focused on responsible generative AI development, do not do service to describe what the companies are doing with AI; they indicate strategic focus, resources invested, and future earning potential. Since AI represents both unprecedented potential and great ambiguity (through regulatory risk, ethical issues, and capital intensity), AI related rhetoric can both increase and reduce the enthusiasm and concerns of investors (Oliveira and Leal, 2025).

The financial markets are more sensitive to such narrative indications (Cave, Dihal and Dillon, 2020). There is a significant amount of empirical evidence that linguistic indicators in disclosures by corporation’s influence stock prices, trading volume (Donelson and Resutek, 2014)and volatility (Dichev and Tang, 2009). However, majority of this literature approaches language on a crude sentiment basis or generally financial dictionaries that had been built long before AI became a dominant strategy theme (Sheng and Shao, 2025). Consequently, the vocabulary peculiarities, ambiguities, and the richness of the topic of AI discourse have not yet been assessed in the frameworks of the existing analytical paradigm (Zatserkovnyi and Teacher, 2025).

This paper is at the crossroads of corporate communication, artificial intelligence, and financial market microstructure. It examines the effect of AI related stories on earnings calls on short term market performance that is, trading volume and volatility, on the five most impactful technology companies listed on NASDAQ (Apple, Microsoft, NVIDIA, Meta, and Alphabet) during the period between the first quarter of 2022 and the last quarter of 2025.

1.1 Statement of the Problem

Even though the strategic and linguistic complexity of AI based disclosure has been determined by previous studies, the existing empirical instruments cannot adequately measure the impact of corporate narratives on investors (Roy *et al.*, 2025). The majority of sentiment analysis in finance is based on either on polarity-based lexicons (positive, negative, neutral) or pretrained transformer models including FinBERT (Satpute, Chatarkar and Sani, 2025). They are useful in general tone classification but fail in the face of new domain relevant vocabulary like “generative models”, “alignment risk”, compute scaling or responsible AI.

More to the point, generic sentiment scores, reduce qualitatively different AI discourse to a measure. The executive statement concerning aggressive investment in AI infrastructure, the discussion of regulatory risk, and the description of breakthrough model performance can all be considered as either positive or negative statements even though their implication on investor expectations is very different (Choi, Huang and Wang, 2025). This thematic flattening obscures the process by which AI narratives influence the behavior of the market (Khalil, 2026).

Concurrently, research on financial linguistics has revealed most studies on long term returns including cumulative abnormal returns or analyst forecast revisions (Wei and Liu, 2025). However, in technology markets where the pace of innovation is high and speculative capital flows are common, the response of investors to narrative signals can be seen in a few hours or days (Doey and de Jong, 2025). Trading volume and implied volatility are especially susceptible to the interpretation and contesting of new information by participants of the market (Liu *et al.*, 2023). Although they are important, such short term indicators have hardly been examined in terms of the thematic content of AI disclosures.

The fundamental issue being considered in this dissertation is thus an empirical and a methodological problem: no clear framework exists that quantifies the effect of various forms of AI narrative in earnings calls on short term investor action, and there is no clear instrument that can be used to connect the said narratives to the immediate market response and market uncertainty.

1.2 Objectives and Importance of this Research

This study aims at creating and using a domain-specific, interpretable framework of analysis of AI narratives in earnings calls and investigating the influence of AI narratives on short term market dynamics. Through building an ad hoc AI lexicon and categorizing executive speech into a set of useful thematic modules, including optimism, investment, performance, uncertainty, and ethical risk, this study aims to get past the generic sentiment analysis into a more specific and economically useful model of corporate speech.

This work is three times relevant. In theory, it expands the discipline of narrative finance by establishing artificial intelligence as a new type of strategic narrative whose impact on the market is inexplicable using traditional linguistic techniques. Methodologically speaking, it adds a transparent and replicable method of textual analysis that is not opaque as black-box models are. In practice, it would provide investors, analysts and corporate managers with a systematic way to understand how AI related communication would tend to affect trading behavior and volatility during the days around earnings announcement.

At this time when market prices start to depend more and more on expectations of technological leadership, as opposed to actual earnings per se, the financial implications of AI stories have ceased to be a luxury, they have become a necessity.

1.3 Limitations and Assumptions

There are some limitations to this study which must be noted to interpret its findings. This study is limited to a sample of five major NASDAQ traded technology companies. These companies are the focus of AI development and commercialization. So, they represent an empirically suitable context. The results of this study might not be directly applicable to smaller companies or to those areas where AI usage is not as developed and evident.

Second, the present research is conducted on the basis of earnings call transcripts as the main source of corporate narrative. The rationale behind earnings calls is that they are full of managerial terminology and futuristic conversation, but this is not the entire disclosure environment of a firm. There could be some other means of communication, like annual reports, investor presentations, or press release that could be used to carry extra information that might not be included in the analysis. Third, AI narrative measurement is based on a lexicon that is custom tailored to standardize and categorize AI related language. Even though this lexicon is based on the theory and previous literature, it is still unable to embrace all potential tints of meaning and contextual interpretation. Like any other text approach, a trade off exists between interpretability and completeness.

Lastly, empirical analysis is done on short term market responses in terms of trading volume and volatility in the market following earnings announcements. Such a design is useful in immediate information processing yet lacks any consideration of more long term valuation changes or post announcement drift. It assumes that intentional managerial communication is present in the language used in earnings call as opposed to random or less purposeful language. It takes additional steps to assume that market participants actively process and react to narrative information revealed in an earnings call. Also, it is assumed that trading volume and volatility are the right proxies to the investor disagreement and uncertainty in the short run in line with the market microstructure theory.

1.4 Definition of terms

To make the study clear and consistent, the main terms employed in the current study are the following:

- **AI Narratives**: Earnings call managerial language referring to artificial intelligence, such as artificial intelligence strategy, investment, innovation, performance implications, uncertainty, and ethical or regulatory implications.
- **Artificial Intelligence (AI)**: Computational systems and methods allowing machines to execute functions commonly referred to as human intelligence such as learning, pattern

recognition and decision making. The term AI in this study only pertains to technologies and applications that are discussed in the corporate earnings calls.

- **Construct:** A theoretical concept that cannot be directly observed but is inferred through measurable indicators.
- **Construct Validity:** The degree to which a measurement instrument accurately captures the theoretical concept it is intended to represent.
- **Custom AI Lexicon**: An organized lexicon of AI related terminologies and phrases created in the present research to group language of earnings calls into specific thematic axes beyond sentiment polarity.
- **Earnings Calls**: Quarterly conference calls where corporate executives meet with the analysts and investors discussing financial performance and strategic developments.
- **Event Level Observation:** A unit of analysis corresponding to a single earnings call and its associated market response window.
- **Lemmatization**: A text preprocessing method that reduces words to their root form by removing suffixes without regard to linguist context or grammatical correctness.
- **Lexicon Based Analysis:** A text analysis approach that quantifies thematic or semantic content using predefined dictionaries of words or phrases assigned to conceptual categories.
- **Market Microstructure**: Financial economics; study of the effects of information in the prices of traded securities, using trading volume, volatility and liquidity.
- **Narrative Density/Intensity:** The number of category specific terms in a transcript, as a percentage of the total word count to enable comparison across documents.

- **Sentiment Analysis**: Text analysis method that classifies the language based on emotional tone; usually positive, negative or neutral.
- **Trading Volume**: The number of shares which have been transacted over a given duration, which in this case is the measure of the activity and the changing beliefs of the investors after announcement of earnings.
- **Volatility**: The extent of change in the price of a stock during a given period, which indicates uncertainty and spread of the expectations of investors. The research is concerned with the short run volatility in the context of earnings announcements.
- A unit of analysis corresponding to a single earnings call and its associated market response window.
- **Winsorization**: A statistical data preprocessing technique that limits the influence of extreme values on outliers by capping values within predefined percentile thresholds while retaining all observations in the dataset.

1.5 Background

The development of artificial intelligence transformed the competitive landscape in the technological industry and beyond (Alsheibani, Messom and Cheung, 2020). AI is no longer placed as a merely an operational tool only but as a strategic capability that affects productivity, innovation, and long term firm value (Lui, Lee and Ngai, 2021). As a results, the topic of communication about AI on the corporate level has become more prominent, mainly when executives discuss strategic priorities or expectations of the investors, primarily during earnings calls. Meanwhile, financial markets have been sensitized towards qualitative disclosures

(Bozanic and Thevenot, 2015). Whereas the old financial metrics like earnings per share and increase in revenues continue to be main components of the valuation, the narrative elements are increasingly applied by the investors to calculate the opportunities in the future (Johnson and Tuckett, 2022). Earnings calls are an important interface between the firms and the market in the sense that they give real time information on managerial intent and strategy (Maia and Bravo, 2026). Although this change has occurred, the current methods of analysis have been unable to keep up with the complexity of the contemporary corporate narrative. The preceding literature largely depends on sentiment analysis to measure disclosure tonality, commonly compressing language to a single dimension of polarity (Sai and Kanikanti, 2024). These methodologies are weak to reflect the complexity of AI related communication, which always presents optimism, investment commitment, uncertainty, and regulatory concern in the same conversation. It is against this background that there is an increasing demand of processes that can be used to systematize and analyze AI related narratives without affecting interpretability and economic sense (Bai *et al.*, 2023). The paper is a reaction to that requirement and is aimed at investigating the impact of AI narratives in earnings calls on short term market outcomes, measured by the trading volume and volatility as a measure of investor disagreement and uncertainty. This work is expected to offer a more subtle perspective on how markets process AI driven corporate communication by incorporating knowledge about narrative finance, artificial intelligence disclosure research, and the market microstructure theory.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter is aimed at building a solid theoretical and empirical base to analyze the impact of artificial intelligence (AI) narratives in corporate earnings calls on short term financial market behavior, specifically, the trading volume and volatility. Even though the present body of literature has concluded that the corporate language influences investor behavior, the sudden appearance of AI as a strategic theme of prominence has radically transformed the nature of financial communication. The executive discourse has changed to the description of intangible assets and incremental product enhancements. Now they talk about the path of abstract technological capabilities, data driven competitive advantages, and algorithmic futures. These changes undermine the current frameworks of financial linguistics and narrative analysis which were mostly constructed during the time when the corporate disclosures were dominated by conventional financial or operational terms.

There is a mix of interdisciplinary literature in this research. It deals with narrative economics, financial linguistics, market microstructure, behavioral finance, and natural language processing (NLP). Collectively, these literatures give the conceptual instruments necessary to grasp the reason why words uttered by executives, and those pertaining to new technologies in particular, like AI are capable of moving markets, changing trading behaviour and redefining risk perception. In the meantime, predictions that are more accurate and more interpretive have been developed with NLP, but a disconnect exists between the financial theory and textual analytics.

This chapter claims that AI narratives are a unique and economically significant type of corporate communication that cannot be sufficiently quantified with the help of generic sentiment scales or commercial language models. The chapter highlights a conceptual gap between the discourse of executives and short term market action based on the work of Romani, 2021 on narrative economics, Loughran and McDonald, 2020 on financial lexicons, and Medya et al., 2022on earnings call texts and stock movements. It also builds on volatility/volume theories, such as the Mixture of Distributions Hypothesis and behavioral financial models (such as the disposition effect, Shefrin and Statman, 1985) to state why narrative signals regarding AI can create immediate, quantifiable effects on the trading activity and the implied volatility.

Thus, this chapter brings together the findings of financial linguistics, narrative economics, market microstructure, and artificial intelligence research to provide a consistent basis of the empirical analysis that is presented afterward. The chapter helps to realize what is already known and what is left open by reviewing previous work on the earnings call narratives, sentiment modeling, AI related corporate disclosures, and short term market responses. Specifically, it underscores the drawbacks of any current sentiment based and black-box NLP method to reflect the thematic depth of AI related discourse, and it points to the lack of studies associating such stories with trading volume and volatility within the immediate post earnings announcement setting. This systematic review thus lays the foundation of the emergence of domain specific AI vocabulary and analysis framework of the upcoming chapters, making this research more than a part of the existing body of literature. Lastly, the definition of this literature review is deliberately focused on large technology companies registered in the NASDAQ, which aligns with the empirical design of the study. The smaller firms or non-technology sectors research was deemed to be less applicable since AI narratives have a different informational value and investor salience in companies like Apple, Microsoft, Meta, Alphabet, and NVIDIA. These companies are also used as worldwide benchmarks when it comes to technological leadership and their profits are followed by institutional and retail investors all over the world. Consequently, their AI stories are more prone to create quantitative volume and volatility reactions, and therefore, a proper subject of interest of this study.

2.2 Inclusion Criteria and Scope of Literature

This literature review is not only aimed at summarizing the existing literature, but to develop a logical intellectual basis of how the narratives of artificial intelligence (AI) in earnings calls can be used to influence the short term financial market performance. To that effect, theoretically based inclusion criteria were used to select the literature based on the interdisciplinary nature of the research problem covering finance, narrative economics and computational linguistics or lexicons.

The initial inclusion criterion was that it had to be relevant to corporate narrative theory. Because this research paradigm views the earnings calls as narrative events but not as an informational disclosure, it will rely on research that considers corporate communication as a strategic, interpretive, and behavioral phenomenon. Articles by Romani (2021) on narrative economics and

Loughran and McDonald (2020) on textual analysis in finance are theoretical foundations of considering the executive language as a type of economic signaling. These researches establish that narratives, analogies, framing, and vocabulary selection are important elements of how to create investor anticipation and market responses. On this basis, only the papers, which explicitly related language to financial behavior were taken and technical NLP papers, which have no financial or economic background, were denied.

The second inclusion criterion was being an event in financial events and empirically engaged in earnings calls. Earnings calls are a special communicative environment where a company is represented by executives who speak about performance and future strategy as well as engage analysts in real time. This environment adds spontaneity, rhetorical, and narrative modulation which are not reflected elsewhere in official regulatory filings. The works of Donders et al., (2000)and Medya et al. (2022) determined that the abnormal trading volume and volatility are linked to earnings announcement, and they concluded that such announcements could be the centers of information processing in capital markets. Meursault et al., (2023) also showed that textual content of earnings calls alone have the ability to forecast post announcement stock movements, as well as when controlling the earnings surprises. These results explain why the study should include the earnings call based research as the empirical cornerstone of the research.

Relevance to the short term market dynamics, specifically trading volume and volatility was the third criterion. The bulk of the narrative finance literature concentrates on long term returns, including cumulative abnormal returns or model analyst revolutions. Nonetheless, the research question that will be tackled in this dissertation relates to the reaction of investors towards AI discourses right after, in most cases, days after an earnings call. Hence, preference was given to those studies that analyze high-frequency or short horizon market responses, including those by Donders et al. (2000), Chen et al., (2001), and Bekaert and Hoerova, (2014) who measure the reaction of volume and implied volatility to new information. Behavioral finance research like disposition effect by Shefrin and Statman (1985) was also added as it describes the interaction of psychological bias with the flow of news to create burst of trading and volatility. Literature that was only interested in long term price efficiency or asset pricing but not in the trading behavior was not taken to be the major scope of this research.

The fourth inclusion criterion involved processing and financial text analysis of natural language. Since in this work, textual data is used to operationalize the concept of AI narratives, it uses research on language quantification and modeling in financial terms. This literature is largely characterized by two general paradigms, namely lexicon-based approaches and transformer-based models. The financial lexicons created by Loughran and McDonald (2020)form a clear, understandable way to transform words into a format of structured variables, whereas FinBERT (Araci, 2019) can be used as an example of deep learning models trained on financial data sets to classify feelings. Nevertheless, transformer models have certain limitations as noted by Wen Tan and Kok, (2023) because they tend to be opaque and not auditable, which restricts their applicability to academic research in which interpretability and repeatability are critical. The studies needed to be within these methodological trade-offs or apply to the financial environments based on earnings calls.

The fifth requirement was AI specific corporate discourse. AI is not just another technological keyword, but it is a qualitatively new kind of strategic communication that combines stories of innovation, ethical issues, capital investment indicators and regulatory risk. Bughin et al., (2017) recorded the accumulation of AI capabilities within large technological companies before the rise of generative AI, whereas (Chubb, Reed and Cowling, 2024) demonstrated that AI narratives themselves were used as a means of social ordering and competitive positioning. Medya et al. (2022) presented preliminary empirical data that the number of AI connected keywords in earnings calls is growing and is related to stock prices. The inclusion of these studies was due to the fact that they clearly relate discourse about AI to corporate strategy and investor perception, and not view AI as an entirely technical artifact.

With regards to exclusion criteria, the literature that was avoided was of various types. To begin with, only purely technical machine learning papers which do not interact with financial communication and investor behavior were eliminated, since they do not inform the narrative-market connection at the heart of this study. Second, no studies were included in which only long term valuation, macroeconomic forecasting, or algorithmic trading were studied without any mention of corporate disclosure since it is not the immediate interpretation processes that are evoked by earnings calls. Third, organizational stories studies that lack empirical evidence in the financial market have been left out since the current study needs quantifiable relationships among language and market results.

The research design is also represented in the temporal range of the literature. When speaking of the time frame since the idea of generative AI and large language models became the focus of corporate levels of discussion, an emphasis was placed on those published since 2017, when AI started to become a strategic narrative among technology corporations (Bughin et al., 2017; Chubb et al., 2024; Medya et al., 2022). Earlier theoretical works, including Shefrin and Statman (1985) and Donders et al. (2000), were incorporated since they become lasting principles in the behavior of investors and market microstructure, which remain true in the age of AI.

2.3 Corporate Narratives and Market Responses

It is well known that corporate communication is a key mechanism by which firms are shaping the belief system of investors and making expectations consistent among themselves. Financial statements only represent quantitative performance. But they are silent about strategic intent, managerial confidence and interpretations of the future risk. These qualitative dimensions are introduced through narratives. This concept is ratified by Romani (2021) in his theory of narrative economics. It states that economic consequences are solely determined by objective information, as well as stories that spread among decision makers. Such narratives are powerful in financial markets when they are told by corporate executives at times of maximum attention, such as quarterly earnings calls.

Some unique aspects of earnings calls are that they are characterized by organized statements. Like the unstructured dialogue between executives and analysts. This combo enables the companies to control impressions, focus on some developments, and rebrand unpromising performance without the strict limits of regulatory filings. This flexibility of narrative explains why Camiciottoli (2010) refers to the earnings calls as a new genre of financial reporting. Tone, repetition, metaphor, and selective emphasis are some of the techniques applied by executives to shape the interpretation of investors about present performance as well as future. By so doing, they do not simply pass the information, but they actively influence the market to understand the meaning of the information.

The importance of such narrative framing is proven by a huge amount of empirical literature. Loughran and McDonald (2020) demonstrated that the words used to make financial disclosures are predictors of market responses regardless of the presence of the conventional financial factors. Their research marked that language is not an aesthetic aspect of reporting, but an economically applicable signal. This understanding was later applied to earnings calls, and it was shown that verbal elements carried in the speech of management are systematically related to investor behavior. An example is Meursault et al. (2023), who have discovered that post-announcement abnormal returns are predictable in textual terms in earnings calls alone, including traditional measures of earnings surprises. The fact that it indicates that the performance talk by the executives can be more informative than the numbers of the performance is especially notable.

Prices are not the only source of the impact of narratives. The trading volume and volatility are also responsive to the manner in which the corporate stories are told. Donders et al. (2000) reported that sharp increases in the trading volume and the implied volatility accompany announcements of earnings reflecting greater disagreement and information processing by investors. Although their research did not dwell into the linguistic content of announcements, it confirmed that earnings calls are occasions when markets actively process new accounts of the direction that a firm is taking. Investors react to new themes presented by the executives, whether these themes are strategy changes, technology changes, or risks, by shifting capital, which is reflected not only in spikes of trading but also in changes in implied volatility.

Behavioral finance can also further explain why the narratives have such immediate effects in the market. According to the disposition effect of Shefrin and Statman (1985), investors are more responsive to bad news rather than to good news, and usually, the investors will move faster to trade when the information in the narrative reinforces or refutes their existing beliefs. When applied in the earnings calls, a positive and confident storytelling can either lead to profit-taking, or even speculative purchasing, whereas vague or warning wording can lead to hedging and volatility spikes. Such behavioural reactions are more pronounced in technology stocks where the valuation is largely pegged on the future innovation prospects, and does not regard the existing earnings as isolated.

The emergence of artificial intelligence has introduced an additional and strong dimension to this narrative setting. Statements that are related to AI are usually indicative of several long term growth prospects, huge capital expenditures, and even regulatory risks simultaneously. According to Chubb et al. (2024), AI narratives can serve as tools of social and competitive hierarchy, which gives companies an opportunity to present themselves as technological leaders or responsible innovators. When the leaders of Microsoft, Meta, or Alphabet speak of their AI abilities, they are not merely selling products; they are narrating a narrative of dominance, credibility, and profitability in the future. These stories in turn affect the way investors determine risk and reward on the days following an earnings call.

The market topicality of this new discourse is empirically justified. Medya et al. (2022) demonstrated that the number of AI related keywords in earnings calls has grown significantly since the emergence of generative AI and that their existence is linked with large post-announcement stock returns. This implies that the market participants do not regard AI narratives as background messages. Since AI is a blend of innovation, uncertainty, and ethical risks, its framing in the narrative will trigger particularly substantial trading and volatility reactions.

This emerging discourse is market-relevant, which is supported by empirical evidence. Medya et al. (2022) demonstrated that AI related keywords in earnings calls have been growing significantly since the introduction of generative AI and that AI related keywords are related to large post-announcement stock returns. This indicates that market participants do not consider AI narratives as a background but as information content. Given that AI is a product of innovation, uncertainty, and likelihood of ethical risk, its storytelling will evoke particularly high levels of trading and volatility reactions.

Collectively, the literature confirms that corporate narratives are a major contributor in influencing the behavior of the market and that earnings calls are the most important places of transmitting the narratives. Nonetheless, the majority of the available research considers language in bulk, without making a distinction among various types of strategic language. This deprives them of a thematic resolution in an era, when AI has become a hallmark of corporate storytelling, leaving an ample chunk of narrative-based dynamics of the market to remain unexplained. This is what prompts the necessity of a more granular analysis of AI specific interest in the impact of executive language on trading volume and volatility in the short run of the aftermath of earnings announcements.

2.4 Sentiment Analysis and its Limitations

There has been a fundamental change in the way researchers and practitioners examine corporate communication due to the increasing availability of textual information in the financial markets. Particular attention has been given to earnings calls as they involve formal disclosure, and interpretation, as well as real-time manager-analyst interaction. Consequently, sentiment analysis has become a prevailing methodological instrument that can be used to convert qualitative discourse into quantitative indicators that could be associated with market behaviors, including price fluctuations, trading volume, and volatility. Although it is a popular method, though, the sentiment analysis literature demonstrates significant conceptual and methodological weaknesses, or rather weaknesses that are particularly poignant in the environment of artificial intelligence (AI)-focused corporate stories.

In finance, the first sentiment analysis was based mostly on dictionary-based methods in early sentiment analysis where a word was categorized as positive, negative, or uncertain. Kearney and Liu (2014) and Luo and Zhou, (2020) surveys record the rise in popularity of these approaches due to their transparency, and replicability, and their suitability with econometric modeling. The financial lexicons by Loughran and McDonald (2020) were a large progress over the generic sentiment dictionaries because words are classified according to financial situations, which minimized systematic misclassification. Their research showed that sentiment which is captured in corporate disclosures is economically significant and associated with market responses making textual analysis a credible aspect of empirical finance.

Nevertheless, lexicon-based measures of sentiment have their limitations of being polarity based and fixed. They make the assumption that words have constant meanings over time and situations, a position which is becoming unsustainable in the eras of dynamic technological revolution. Language complexity in earnings calls, of which it is not simply positive or negative, is statistically significantly related to volatility as (Alan, Engle and Karagozoglu, 2023a) demonstrate. The implication of this finding is that besides the direction of sentiment, the market also reacts to ambiguity, abstraction, and interpretive challenge inherent in managerial language. Such dimensions cannot be well captured in static dictionaries especially when firms are talking about new technologies whose meanings are being negotiated.

The emergence of machine learning and transformer-based models is an effort to eliminate such constraints. FinBERT, first proposed by Araci (2019) and then optimized Huang et al., (2023), uses contextual language modeling to financial text and therefore the sentiment classification relies on previous words and sentence structure. Comparisons on an empirical basis demonstrate that sentiment measures based on machine learning tend to be more predictive than dictionary-based methods especially when large and heterogeneous corpora are involved. Frankel et al., (2021) also show that machine learning models can identify disclosure sentiment hidden in the nuances, which are hard to identify with the help of traditional lexicons.

However, this performance advantage will be at a price. Models that use transformers, behave typically as black boxes and, therefore, there are hard to trace the predictions to individual linguistic features. According to Hoberg and Manela, (2025), this obscurity prevents the applicability of such models in the financial research field, where the ability to interpret is crucial to theory development, replication, and regulatory analysis. This is a very troublesome limitation in the case of earnings calls. When volatility soars after an announcement, both researchers and practitioners are interested in knowing why-was it the response to investment commitment, uncertainty caused by regulation, ethical issues or a threat of competition. There is a dearth of information on these mechanisms provided by black-box sentiment scores.

A major similarity between lexicon-based and machine learning-based sentiment methods is that they simplify language to a single think-dimension. This minimization clouds the fact that corporate disclosures are usually multiple and even contradictory in what they say. Miller and Piotroski, (2000) demonstrate how forward-looking statements may be both optimistic and at the same time, add uncertainty regarding future events. Giammarino et al., (2004) also state that managerial language is able to push and pull the prices as well as react to the earlier market motions which makes it more difficult to interpret causal relationships. Such dynamics are particularly acute in the case of technology companies, where long term innovation is frequently the theme of strategic stories, with short term execution risk being taken into consideration.

The weakness of the polarity-based sentiment measures is further amplified by the fact that companies are talking about artificial intelligence. Disclosures related to AI are often filled with excitement about productivity and competitive advantage and restraint regarding regulation, ethics and heavy capital. According to Scholes, (2025), AI can be described as a source of so-called structured uncertainty, which poses risks that cannot be easily priced by conventional financial models. In a similar manner, Bory et al., (2025) differentiate between "strong" AI narratives which focus on the transformational potential and "weak" narratives which focus on the control and restraint. The discursive appearance of such discourse is homogenously positive in a manner that masks its internal composition and waters down its explanatory strength.

This is criticized in recent empirical studies. The study by Alan et al., (2023) reveals that the linguistic complexity of earnings calls is positively correlated with the volatility, which indicates that markets respond to an interpretive difficulty and not sentiment. Qin and Yang, (2019) demonstrate that verbal and vocal cues of what the managers say and how they say it lead to volatility prediction. The NLP-based sentiment analysis of earnings calls and stock volatility study also supports the idea that the features of the narrative other than sentiment polarity have significant contribution in the explanation of volatility reactions. All these results suggest a mismatch between the abundance of corporate language and the simplicity of dominating sentiment scales.

According to these problems, there has been an emerging school of thought in the literature that supports more explainable and thematically organized methods of financial text analysis. Rizinski et al. (2024) present explainable lexicon-based models which are both interpretable and permit more contextual variability. According to Wen Tan and Kok, (2023), explainability is not just a desire but a methodological imperative of financial research. Similar findings are expressed by Hendre et al. (2025) who report that the concept extraction techniques used on the earnings call transcripts present more detailed versions of managerial intent compared to the aggregate sentiment scores.

Collectively, the literature would indicate that sentiment analysis, though a basic one, is inadequate in reflecting economic value of AI based business stories. Lexicons that are not dynamically updated to changing technological language are not dynamic, and models built using black-box machine learning do not have interpretability at the expense of predictive performance. Which is why neither methodology properly separates the various forms of AI related discourse that can have different implications to investor behavior. This shortcoming of the methodology is the primary reason why they should create a custom, AI oriented lexicon with a greater emphasis on thematic differentiation and transparency in order to be able to more accurately study how the language used by executives affects trading volume and volatility during the direct aftermath of the earnings calls.

2.5 AI in Financial Disclosure and Corporate Strategy

AI is now at the heart of strategic disclosure, especially in the case of big technology companies. The valuation of tech companies strongly depends on the anticipations around innovation leadership. As opposed to the previous waves of technological change, AI is not positioned as a productivity enhancer or a support “feature” only. It is becoming more and more positioned as an enabling feature that changes the business model, competitive lines, and future growth paths. The implications of this shift have significance in the area of financial disclosure as it changes what firms want to disclose and the manner in which investors will perceive the disclosures.

In the view of disclosure, AI related language is a prospective indicator. Miller and Piotroski (2000) prove that forward-looking statements of corporate disclosures have an impact on market response as they project expectations of future performance even where current financial outcomes are identical. These futuristic aspects are particularly relevant in the context of AI as most AI investments do not make immediate revenue, but are explained by the narrative of scalability, learning effects, and a future-dominating force. Subsequently, the earnings calls have turned into one of the main platforms where executives explain the strategic justification of the high AI related spending and frame them as value-generating instead of expensive.

According to Damodaran, (2017), valuation is more about a narrative exercise backed by the numbers than vice versa. This observation is applicable when it comes to AI disclosures, in which conventional accounting metrics are frequently behind their strategic reality. The capitalized assets do not represent the real economic worth of proprietary models, data infrastructure or organizational learning. Therefore, managers use narrative to close the gap existing between current financial statements and future cash flows. AI stories are then a tool of resolving the beliefs of the investors with managerial visions of long term value creation.

The strategic significance of AI related disclosure is supported by the recent literature on the basis of empirical evidence. As Cao et al., (2023) demonstrate, corporate communication will adjust when companies expect that the disclosures will be handled independently not only by algorithms but also by human investors and, as a result, change its tone, structure, and focus. This observation indicates that AI is not only impacting the process of disclosure as a discussion but also as a contextual driver of disclosure and how disclosures are being made. Simultaneously, Gao et al., (2023) report that the use of AI is linked to productivity increases from the firm-level, which is why the managerial arguments stating that AI investments would result in some actual profit in the economy have a basis of supporting evidence.

Nevertheless, AI disclosures are not entirely positive. According to Scholes, (2025), AI brings to the financial markets a unique type of uncertainty that is a combination of technological risk, regulatory ambiguity and ethical concerns. These risks tend to be explicitly noted by the executives on earnings calls, with models addressing problems relating to data governance, model bias, and the need to adhere to new regulatory frameworks. According to Al-Okaily, (2024), AI revelations in the accounting setting are becoming more focused on transparency and accountability as a result of the expanding stakeholder examination. These warning signs are intertwined with the stories of innovation and growth, and they provide disclosures, that are internally complicated and hard to categorize in terms of simple measures of sentiment.

There is also no uniformity in how AI stories are strategically implemented by firms and situations. Bory et al., (2025) suggest that the analytical difference between the strong and weak AI narratives should be based on transforming potential and unavoidability in strong AI and control, governance, and incremental integration in powerless AI. This model is especially effective in the context of earnings call discourse where executives can switch with bold assertions and more moderate promises based on the shareholder fears, the competition, and the regulatory landscape. This type of narrative modulation aligns with the opinion expressed by

Giammarino et al., (2004) that market conditions do affect and are reflected in managerial communication in a feedback loop.

The application of AI related discourse in terms of its applicability to the market can also be emphasized by using empirical studies that concentrate on earnings calls. These three authors demonstrate that the complexity of earnings calls language is positively linked with volatility, indicating that the markets respond not only to the information in the disclosures, but also to the effort involved in interpreting it (Alan et al., 2023). The paper released in International Journal of Artificial Intelligence, Business and Data Communication Management Studies on NLP-based sentiment analysis of earnings call also reveals that narrative properties obtained, based on call transcripts, are useful in explaining post-announcement volatility reaction. This finding means that AI related disclosures, characterized by their use of technical terms and abstract concepts, would lead to increased trading activity and volatility because of the increased interpretive uncertainty.

The use of AI stories also contributes to the perceptions of competitive positioning. Bughin et al., (2017) record that the artificial intelligence capabilities are concentrated in few firms, which supports the dynamics of winner-takes-all. When Apple, Microsoft, Alphabet, Meta, or NVIDIA executives speak of AI strategy, investors can take such words as a sign of relative technological leadership, but not absolute performance. Robertson and Maccarone, (2023) go on to state that AI narratives help create unequal conditions by making specific actors plausible innovators, a formula that can increase market responses to AI related announcements by big companies.

Collectively, the literature indicates that AI related financial disclosure functions on various strategic levels. It contains information concerning projected productivity improvements, sends information concerning long term investing commitments, and controls the uncertainty that surrounds regulation and ethics, and places firms in a competitive pecking order. These dimensions tend to be mixed within the same earnings call, with the creation of rich yet hard to separate narratives. This complexity cannot be well-represented by the traditional sentiment analysis where disclosure is collapsed into a single score of polarity.

This literature inspires the desire to have a more granular analytic framework that considers AI disclosure a multi-dimensional narrative, as opposed to a homogeneous sentiment signal. The current research contributes to the disclosure theory and the study on strategic communication by breaking down AI related language into thematically specific categories, including innovation, investment, performance, uncertainty and ethical risk, as to determine how various aspects of AI related conversation relate to short term market effects. It is a better way to give a more precise connection between corporate strategy, executive language and visible market results and preconditions the methodological framework in the following section.

2.6 Conceptual Framework: Lexicon Based Textual Analysis

The intense spread of artificial intelligence into financial markets has increased the demand of analytical approaches that are accurate, as well as understandable and scientifically justified. Since AI driven scripts continue to enter the earnings calls, the methodological challenge facing researchers is no longer whether textual data is analyzable, but how it ought to be analyzed in a manner that maintains economic significance and leads to causal conclusions. The section contains an argument that lexicon-based textual analysis, when tailored to both thematic specificity and domain understanding, provides a relatively appropriate structure of analysis of AI narratives in earnings call, particularly in comparison with the opaque language models.

The explainability is also identified as a major limitation when using AI techniques in finance by a growing body of literature. (Cao, 2022) identified interpretability and regulatory responsibility as ongoing issues that restrict the use of sophisticated machine-learning models in high-stakes financial decision-making in their extensive review on the use of AI techniques in financial services. These issues are particularly pertinent in the context of the disclosure based research when the empirical results must be justified to the academic community as well as practitioners and regulators. In this respect, the approach which enables researchers to trace the consequences of linguistic characteristics is not only desirable, but also obligatory.

Lexicon oriented methods meet this need by establishing a clear mapping of language and constructs of analysis. Previous research by Cecchini et al., (2010) showed that words in a financial text may be used to predict financial events and therefore textual analysis was a good empirical method long before deep learning came into existence. This theoretical observation applies equally to the present day context, especially to earnings calls which still constitute a specific type of disclosure that is marked by managerial freedom and rhetorical reporting Camiciottoli, (2010). Lexicons allow the researcher to encode these rhetorical options in a systematic manner and correlate them with market behavior.

The creation of domain specific lexicons in the field of financial research was an important methodological breakthrough. Loughran and McDonald (2020) demonstrated that institution-specific financial dictionaries are effective at lowering semantic misclassification and outcompete generic sentiment tools by a significant margin. Nevertheless, there is later evidence that even finance-specific sentiment lexicon is limited when used with technologically complicated disclosures. Khoo and Johnkhan, (2018) assessed that various sentiment lexicons tend to produce materially different outcomes, as well as emphasizing how sentiment is not a consistent or universal concept. The result is especially consequential in the context of AI related discussion in which terminology changes very quickly and has many context specific meanings.

The scientific observations also indicate that market agents react to the aspects of language that go beyond sentiment polarity. Alan et al. (2023) demonstrate that earnings call linguistic complexity has a positive correlation with volatility, which reveals that interpretive difficulty per se can be the source of information about uncertainty. On the same note, Qin and Yang (2019) conclude that managerial speech is predictive of volatility, regardless of sentiment direction, because of both verbal and structural cues. These outcomes suggest lessening of disclosures to either positive or negative tone can be dangerous in the sense that it may be overlooking important narrative processes that drive trading actions.

Machine learning and large language model (LLM) based methods can be used to overcome these challenges because they are more able to capture contextual subtleties and semantic connections than traditional lexicons. Siano (2025) shows that high predictive power can be discovered by using the context of words in earnings announcement disclosures using the methods of LLM. However, these methods are still weak in giving clear explanations on effects that we observe. The transparency of LLMs makes their application in environments that need the interpretability, auditability, and theoretical coherence difficult as Cao (2022) and (Trachova *et al.*, 2026)explain. This opacity limits the potential to connect linguistic characteristics with particular economic processes in hypothesis based research.

The recent methodological work thus has tended to lean towards a hybrid view which puts a greater emphasis on explainable, thematically structured analysis. Rizinski et al., (2024) demonstrate that frameworks of explainable lexicon can maintain transparency and at the same time be contextually sensitive may compete with machine learning dominant systems in explanatory abilities. Similarly, Hendre et al., (2025) prove that concept based extraction of earnings call transcripts is a better representation of managerial intent in comparison to aggregate sentiment scores. Cross domain experiments add further evidence to the trade-offs between interpretability and performance in lexicon and machine learning based sentiment analyses and therefore support the argument of making methodological decisions that are based on the purpose of the research and not necessarily on predictive performance (Qi and Shabrina, 2023).

2.7 AI Narratives and Market Signaling

The literature reviewed thus far points to a common conclusion that corporate language has a significant effect on financial markets, but is still disjointed in conceptualizing, measuring and connecting language to the behavior in the market. Although previous research confirms that earnings calls influence investor responses, analytical paradigms and models are becoming increasingly skewed with the format and content of the modern disclosures, especially artificial intelligence based disclosures. Such a misalignment is not only methodological, but it also impairs the capacity of the present research to describe the role of AI narratives as market relevant signals.

The enduring weakness of literature is the consideration of language as a relatively one dimensional phenomenon. Narrative finance and disclosure research generally operationalize managerial disclosure in terms of aggregate tonality or optimism, implicitly attributing the primary responsiveness of investors to the valence of emotional communication. Sentiment analysis formalizes this hypothesis by providing scalable metrics that are polarity based. Nevertheless, AI disclosures do not conform to this method. The discourses of AI that are run by executives seldom send a unidirectional message; they consist of ambition, caution, long term vision and immediate constraint, opportunity, and risk. Declaring this language to sentiment polarity reduces different informational clues to a token that cannot be differentiated, and therefore, the way language influences market action becomes obscured.

Research about AI in financial disclosure highlights this gap. Sentiment based methods (lexicon or machine learning) are meant to provide the answer to the question is the language good or bad. They do not capture the type of information being conveyed. This difference is essential in the conditions of AI. The use of a language that emphasizes on AI investment might create uncertainty when it comes to cash flow, even though it could signify that there is growth potential. Similarly, discussions about ethical AI and regulation may dampen tail risk while adding to the short term ambiguity. Narratives of innovation can trigger speculative trade, and those that are characterized by uncertainty can enhance the level of disagreement amongst investors. The use of these signals become incompetent in treating a signal that is fundamentally different and binary (yes/no).

With these limitations, a thematic narrative standardization turns out to be a motivation to replace sentiment measurement. An artificial, AI denoted lexicon provides a systematic way of operationalizing AI speech, giving language defined economically, i.e., in dimensions of innovation, investment, performance, uncertainty, and ethical or regulatory risk. This approach standardizes heterogeneous disclosures into comparable constructs grounded in theory and does not merely quantify language. By so doing, it allows systematic tracking of the dynamics of the narrative of AI related narratives, as adopted in firms as well as through time, without compromising interpretability and replicability.

The standardization is especially relevant because of the nature of earnings calls. Compared to statutory filings, earnings call is conversational, flexible and mainly contextual. The standardization is especially relevant because of the nature of earnings calls. Compared to statutory filings, earnings call is conversational, flexible and mainly contextual. Managers are dynamic in responding to the questions of the analyst, they focus on the chosen themes and discuss narrative framing according to the perceived market concerns. Unless a systematic scheme is in place, one will succumb to the temptation of making such discourse ad hoc and generalized. An analytically rigorous lexicon also brings about analytical discipline, where measurement is based on the same criteria and not subjective.

This framework is further enhanced by the emphasis on the trading volume and volatility. Much of the available literature focuses on price or determined results, which implicitly presupposes that disclosures are more about directional information of a firm's value. But the stories about AI are going to be more likely to create uncertainty to disapprove rather than an instant agreement. According to the theory of market microstructure, the conditions are best manifested in terms of trading volume and volatility which reflect the strength of updating of beliefs and spread of expectations among investors (Karpoff, 1987). These indicators consequently give a closer prism through which to view the direct market processing of information relating to AI.

Notably, the motivation of the selection of volume and volatility is diagnostic rather than novelty. An earnings call can create significant trading without a clear direction in the price movement, which displays a difference in the meaning of AI strategy instead of being a valuation consensus. On the same note, the volatility can also rise after AI intensive disclosures despite positive financial performance, indicating the uncertainty regarding strategic implementation, regulatory risk, or the future. With such outputs of microstructures, the study can capture the aspects of the market response that possibly are not captured by analyses that are based on prices.

The synthesis of these strands indicates an apparent gap in the literature that is consequential. The current research proves that language is important, sentiment is quantifiable, and AI has become the focal point of corporate strategy. However, there is no unified structure at present that AI related language standardizes and empirically correlates the categories with short term market microstructure performance on the basis of earnings call disclosures. This gap reflects the disengagement of the complexity of AI discussion with the simplicity of the tools of analysis.

The current paper fills this gap by formulating a tailored AI oriented vocabulary and using it on the earnings call transcripts of major technology companies. The study is more accurate in its immediate short term impact of AI narratives on investor behavior by leaving emotion behind in favor of measuring the performances of the stock market theoretically, i.e., the volume and volatility that ought to be expected of the stock market in response to AI narratives. This way, it connects narrative finance with AI disclosure studies and market microstructure theory and forms a consistent basis on the empirical methodology in the next chapter.

CHAPTER 3

RESEARCH METHODOLOGY AND EMPIRICAL DESIGN

3.1 Conceptual Approach to Measuring AI Narratives

Present work assumes the strategically grounded approach to the measurement of artificial intelligence (AI) narratives in corporate earnings calls. A strategy of what is defined as active and managed managerial language in circumstances of a lack of information asymmetry. The methodology does not consider the discourse of earnings calls as either the expression of generalized sentiment; but instead, an AI related language is a constellation of intentional cues that help firms display strategic intent, show commitment, and deal with ambiguity. The conceptualization motivates a multi-dimensional measurement structure that divides the narratives of AI into discrete units.

Earnings calls create a disclosure setting of utmost importance where managers relay forward looking stories to investors and analysts on a real-time basis. Past studies have determined that the informational nature of earnings calls goes far beyond the quantitative financial information, and the narrative framing is at the center of market construing, trading, and volatility (Frankel et al., 2021; Cecchini et al., 2010). The strategic importance of narrative communication is especially acute in the environment of AI, a new general purpose technology with high uncertainty, high capital intensity, and constantly changing regulatory control.

This study has been driven by the conceptual approach which adopts the strategic management theory, economic signaling theory, narrative economics, and resource-based view of the firm. A combination of these views makes up a consistent theoretical explanation when focusing on classifying AI related earnings call discourse based on its strategic role and the way it is expected to be understood in the market.

3.1.1 Strategic positioning and Communicative Choice

Strategic positioning theory emphases that competitive advantage is determined by intentional decisions in terms of positioning, differentiation, and trade-offs. According to Porter (1996), a strategy is simply a matter of what should be done and what should not be done, and these decisions are shown through the regular patterns of organizational behavior. Corporate communication is part of such patterns, specifically investor facing environments like the earnings calls.

This interpretation implies that talking about AI projects by executives is a tacit indication of how AI is integrated into the overall competition strategy of the company. The purpose of differentiation is found in stories that emphasize AI innovation, but the reference to AI investment suggests long term strategic investment. References to AI performance credence performance, but recognition of uncertainty or regulator constraint would be conscientious realization of strategic constraints. The categorization of AI narratives based on strategic role thus operationalizes the positioning of AI in the competitive logic of firms and does not eliminate such discourse as undifferentiated tone.

3.1.2 Under Asymmetric Information Signaling

The economic signaling theory is another pillar to be applied in the conceptual approach of the study. The signaling theory of performance of asymmetric information introduced by Spence (1978) illustrates that the cost, credibility, and observability of signals in the market are considered to interpret them. Worth noting that the signals are not produced in equal manner. And their informational content varies with the amount of effort or sacrifice involved in creating them.

The use of AI in earnings calls works as heterogeneous signals. Statements which focus on the AI innovation or vision, are those which have low signaling costs and are possibly aspirational positioning. On the contrary, the data on the investment of AI, such as the capital investment, the volume of assets (infrastructure), or resource deployment, correspond to higher signaling costs and, therefore, commitment. Similarly, narratives of AI performance offer visible rewards, and dialogues about uncertainty or ethics and regulation can serve as expensive buzz about transparency and knowledge of governance.

This signaling approach explains why generic sentiment analysis cannot theoretically be used to analyze AI disclosures. A one dimensional sentiment score is not able to distinguish between low cost visionary signaling and high cost commitment signaling. Same applies to opportunity framing and risk recognition. The study coordinates its measurement strategy to well-developed economic theory regarding the processing of corporate communication in markets by classifying AI stories as either signaling a task or not.

3.1.3 Narrative Economics and Differentiation by Themes

Narrative economics also lends to the necessity of adopting a multi-dimensional approach to the assessment of the AI discourse. Shiller (2017, 2020) asserts that the spread and interpretation of narratives drive economic outcomes; the theme of the narratives varies in their persistence and resultant economic implications. The change brought about by a narrative does not only depend on its being positive or negative, but on what the story is and what it changes in expectations.

Earning calls use AI stories with several, even contradictory themes of technological potential, performance, investment, risk taking, and social responsibility. The approaches based on treating such discourses as one dimension of sentiment do the risk of withering the mechanisms by which AI narratives can affect investor behavior. By organizing AI related language into thematic units, these plots can be measured independently and empirically associated with market performance, and narrative economics can be applied to the empirical study of corporate disclosure.

3.1.4 AI as a Strategic Resource

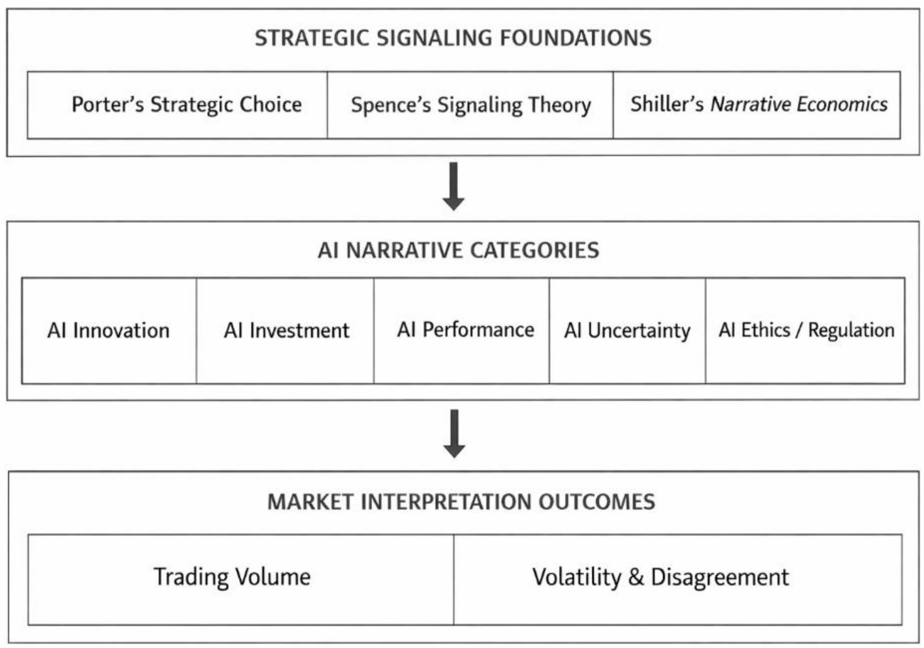
Resource-based perspective on the firm presents one more perspective according to which AI stories can be seen. In a conceptualization of sustained competitive advantage, (Barney, 1991) presents the idea as such an occurrence due to resources that are valuable, rare, not easy to imitate and well organized. These resource characteristics are often implicitly covered in corporate discourse about AI, as much as it seems to be a resource of value generation, an object of continued investment, a driver of performance, or a field with limits defined by regulation and ethical concerns.

These dimensions are reflected in the communicative form by the AI narrative categories used in this research. Value creation is addressed by innovation narratives, resource accumulation by investment narratives, realized advantage demonstrated by performance narratives and imitability constraints and institutional legitimacy addressed by ethics and regulation narratives. In this respect, the lexicon operationalizes the communication that companies make regarding AI as a strategic resource and not a technological one.

3.1.5 Measuring Strategy to Conceptual Framework

Together these theoretical viewpoints combine to encourage a conceptual method. Therefore, AI involved language in earnings calls is dissected into strategically pertinent narrative categories, with each category having a specific interpretation in the market. This method views narrative measurement as a strategic signal as opposed to sentiment deconstructing. The resulting set of rules forms the basis of creation of a tailored AI lexicon that can be our main tool in the process of translating qualitative disclosure into quantitative variables.

Figure 3.3 Conceptual Framework



Source: Author's own elaboration

This methodology is based on a foundational theory and incorporates the importance of transparency and interpretability, which will allow future empirical research to be supported by meaningful association with managerial communication practices and investor response processes. The next few sections expand on this conceptual basis explaining the research design, data preparation and lexicon construction processes used to operationalize this conceptualization.

3.2 Research Questions and Hypotheses

Expanding the conceptual framework described in Section 3.1, this paper formulates its research question by a series of specific research questions and testable hypotheses. The intent is to encapsulate the strategic and narrative rationale of AI based corporate communication into empirically determined connections between earnings call speech and transient market action.

The quick materialization of artificial intelligence as a core business instrument, more so among large technological companies, has made the subject matter of AI based language within the earnings calls a marginal issue to be discussed by the executives as a topic. Such narratives are more frequently used in lieu of actual performance measurements as firms talk about new technologies where there is uncertainty, prolonged payback period, and changing regulatory restrictions, as discussed in Chapter 1 and the conceptual section above. Although becoming increasingly noticeable, AI narratives remain not analyzed in a structured way and have not been empirically correlated with instant reactions of the market by use of transparent and reproducible way.

In this connection, the four related research questions direct this study and respond to both the substantive effects of the market and the contribution to the research methodology.

Research question 1: Are AI related narratives in earnings calls associated with increases in short term trading activity following the announcements?

To begin with, the research question is whether the AI related narratives that are announced in the earnings calls have a quantifiable impact on the short term market patterns. In particular, it is analyzed whether a difference in AI concentrated language is correlated with abnormal increases or declines in the volume of trading and the implied volatility in a small behavioral range around a period of earnings announcement. In asking this question, the focus of interest is no longer on long term effect on valuation but rather on high frequency investor responses, in which narrative interpretation has the highest chances of showing quick responses.

Research question 2: Are uncertainty oriented AI narratives associated with increases in short term implied volatility?

Second, the research question is whether the various thematic categories of AI narratives are linked to unique market reactions. As opposed to perceiving AI discussion as a homogenous entity, the analysis identifies topics (narratives) with more focus on innovation, investment, performance, uncertainty, and esteem or regulatory issues. The question indicates a presumption that not all the AI related language will be reacted by the markets evenly but rather the investor response will be based on the strategic significance and level of believability of the underlying story.

Research question 3: Does a custom AI lexicon provide greater explanatory power than generic sentiment models in explaining short term market reactions?

Third, the research examines the methodological trustworthiness and interpretation power of a natural language processing framework of custom lexicon. Current sentiment models, such as general financial lexicons and pretrained transformers based (FinBERT) systems, are largely used to categorize text by major polarity metrics, and are insensitive to any emerging AI specific terms. The research question evaluates the hypothesis that the thematically arranged domain specific AI lexicon can better measure AI discourse in earnings calls and predict short term market behavior in such a way that it is transparent and understandable.

Lastly, the paper takes into account the real world practical application of this custom lexicon analysis model to those in the markets. Connecting definite categories of the AI narrative, through which changes in the trading activity and volatility could be observed, the study aims at creating a piece of insight that may be used in the context of interpreting it by an investor, evaluating it by an analyst, and planning its communication by a corporation. The research also makes sure that the study is not limited to academic modelling only.

H1: AI related stories are somehow connected with the high level of trading during a short period.

The hypothesis of the study is the first hypothesis that the intensity of AI related narratives has a positive relationship with the short term trading volume. The trading volume is commonly understood as an indicator of investor attention and disagreement, especially enormous events, associated with information, like calls to discuss the earnings. To the degree that AI stories need more careful attention or varied understanding, they will be associated with a rise in trading.

H2: Uncertainty oriented AI narratives have a positive relationship with an increase in the short term implied volatility after earnings announcement.

The second hypothesis is based on AI narratives with greater emphasis on uncertainty, such as mentions of regulatory risk, ethical issues, technological constraints, or unresolved implementation issues among other themes. The preliminary studies of disclosure theory and market microstructure indicate that these stories create ambiguity regarding future returns and spread the beliefs of investors. Under such circumstances, as executives anticipate uncertainty in their AI discussion, they can encourage investors to re-examine risk, re-adjust expectations, and even adopt hedging behavior, especially in the short term after earnings announcements. Consequently, the uncertainty oriented AI stories are supposed to be linked to high means of implied volatility in the short term. Although the analysis considers the volatility response to all AI narrative categories, uncertainty themed narratives are postulated to have the strongest and most systematic association with the implied volatility because they are directly related to risk perception.

H3: A specially designed AI lexicon based framework leads to a higher level of explanatory power on short term market reactions as compared to generic sentiment based models.

The third hypothesis relates to the methodological value of the work since it assesses the performance of a tailored AI lexicon in comparison to generic sentiment-based models. The conventional sentiment analysis instruments mostly group text according to the general polarity scales and do not necessarily focus on the strategic and thematic peculiarities of AI related business communication. The given lexicon, on the contrary, clearly separates AI narratives based on their strategic role, allowing to conduct a more interpretable and theoretically-based evaluation of the connection between various narrative themes and market reactions. This hypothesis does not focus on predictive accuracy by itself but points at explanatory relevance, interpretability, and theoretical consistency as major measures of model effectiveness. The analogy then is whether the custom lexicon can offer adding value to the explanation of short term market responses over and above a generic sentiment measure.

These research questions and hypotheses provide a purposive analytical approach leading to strategic AI stories all the way to the real life market results. They provide internal consistency among the conceptual backgrounds presented in Section 3.1, the empirical design presented in the following parts, and the overall aims of the study to contribute to the narrative finance and provide practical implications to market participants.

3.3 Sample Selection and Study Scope

The research paper will concentrate on a specific sample of large, publicly traded technology companies where artificial intelligence has already turned into the key element of strategic communication and capital investment. In particular, the sample will include five most popular NASDAQ listed technology firms, such as Meta Platforms, Microsoft, Apple, Google (Alphabet), and NVIDIA. These companies were chosen due to their long term and active investment in AI technologies, their active mentions of AI in investor facing reports, and their significant impact on the overall market mood and the dynamics in the technology sphere.

The selection of this sample is based on theoretical and practical reasons. Theoretically, companies on the technological edge have a higher probability of using narrative disclosures to address new capabilities whose economic worth is unpredictable or long term in relation to them. The performance of AI related initiatives does not always have clear, immediate performance metrics, which raises the need to rely more on managerial narratives to express strategic intent, commitment, and expected results. Consequently, the earnings calls of such companies offer a highly valuable opportunity to study the construction and perception of AI stories by the financial markets.

Practically, these companies are characterized by a high trading volume and analyst coverage, so earnings calls are events with a high level of information content and instant effects in the market. Both institutional investors and retail investors pay close attention to their disclosures, so it is more likely that narrative information is quickly integrated into trading behavior and volatility. This predisposes the chosen companies to the study of short term responses to AI related communication in the market.

The selected firms are identified as AI frontier firms based on a combination of firm disclosed strategy and investment metrics and corroborating industry analyses that were studied as part of this research. The company investor relations' materials and recent SEC filings explicitly reference AI strategy and investments, quantified indicators such as R&D and capex levels, patent activity and AI related acquisitions, and third-party assessments of AI leadership by leading consultancies and financial analysts.

The study time range is a few fiscal years, as it involves all the quarterly earnings calls between 2022 and 2025. The carved out period represents the onset of increased AI adoption and increased interest among the population and investors due to the progress in the field of large scale machine learning and generative AI technologies such as LLMs. Through a series of quarterly calls of individual firms, the study can enable shift of AI narrative intensity and thematic focus over time while retaining a focused dataset aligned with the research's explanatory objectives.

The sample will be defined by calendar based earnings call announcement dates between January 2022 and December 2025. The design is based on the fact that the firms used in the study have disparate fiscal calendar, which reflects the strategic, historic and operational aspects as opposed to similar reporting conventions. As an example, Apple uses a fiscal year ending in September, so that the first fiscal quarter of the year captures the major sale period around the holidays, whereas companies like Microsoft and NVIDIA have fiscal schedules that do not align with the calendar year because of past reporting practices, business cycles and industry factors. Such differences are usually due to efforts to match reporting periods to product cycles, supply chain timing, or established practices of corporate governance as opposed to substantive differences in strategic behavior. Since the current research looks at the short term market responses to the earnings call narratives, the temporal point of reference of the current research is the actual time of disclosure as it is felt by the investors in the calendar time. The implication of volatility is that trading, suggested volatility and wider market signals react to announcements dates and not to fiscal labels. As a result, the fiscal quarter names are left in the form of descriptive metadata but not as the inclusion criteria, so that all the observations are synchronized to the same market-oriented timeframe but transparency in terms of firm-specific reporting frameworks is maintained. This strategy is a compromise between comparability between firms and faithfulness to the actual market process, where narrative effects can be measured in a consistent timeframe despite the varying accounting calendars.

This calendar based event design also does not force an artificial balance structure on firms whose reporting cycles are natural asynchronous. The study maintains the natural informational setting in which investors construct earnings stories by grounding observations on the timing of disclosure events, as opposed to fiscal-quarter alignment. Consequently, the time variation in reporting gets regarded as a genuine feature of real life market communication, instead of providing a methodological distortion. The empirical design is thus consistent with the explanatory purpose of the study to explain the immediate investor interpretation of AI related stories.

Table 1 summarizes the differences in fiscal year-end structures across the sampled firms, illustrating why earnings call announcement timing does not align uniformly with calendar quarters.

Table 3.1 Fiscal Year End Structures Across Sampled Firms

Company	**Fiscal Year End**	**Typical Timing of Q4 Earnings Call**	**Relative Timing Pattern**
NVIDIA	January 31	February	Fiscal reporting offset from calendar year
Apple	September 30	October/November	Fiscal year shifted to align with product cycle
Microsoft	June 30	July	Mid-year fiscal cycle
Alphabet	December 31	January/February	Calendar year aligned
Meta Platforms	December 31	January/February	Calendar year aligned

Source: Author’s own elaboration

The individual earnings call event is the unit of analysis. AI related narratives are extracted on each earnings announcement based on the relevant earnings call transcript and correlated with short term market indicators calculated within a small event window around the earnings announcement date. This event based design assumes that the interpretation of the narrative and market response are most acute when observed in close time proximity to the announcement.

In order to retain the analytical focus, this research purposefully limits itself to a limited number of companies and time. The research has no intention of generating population-wide estimates of the AI narrative effects of all firms or industries at this point. It rater aims at offering an indepth understanding of the mechanism of AI related narratives operating in the context in which these kinds of revelations are most prominent and impactful.

The chosen sample and the event-oriented design allow this analysis to create a consistent empirical background to study the relationship between AI narratives, trading volume, and volatility. This scope provides a base to the next steps of data preparation, narrative measurement and empirical modeling. Those details are discussed in the following sections.

3.4 Earnings Call Data Collection and Preparation

The research utilizes the earnings call transcripts as the major source of qualitative disclosure information. Earnings calls are formal, regularly recurring meetings where the senior management communicates the performance of the firm, its strategic focus, and future initiatives directly to analysts and investors. They constitute an information-rich disclosure setting in which artificial intelligence-related narratives are articulated, contextualized, and interpreted by financial markets.

3.4.1 Source of Transcripts and Time Period

Transcripts of earnings calls were downloaded from publicly available investor relations website. ‘Seeking Alpha’ has credible financial information sources that store quarterly earnings announcements. In the case of each firm, transcripts of all quarterly earnings calls during 2022 to 2025, including fourth-quarter disclosures, were received. There were several available transcripts of a particular earnings call, ones that maintained the names of speakers, the chronological flow and the full discussion were prioritized. The matching of the transcript to the date of the respective earnings announcement was done accurately. This ensured that the transcripts are correctly aligned with the market data applied in the empirical analysis study. This time frame consistency is crucial towards ensuring integrity of the event based research design used in the study.

3.4.2 Scope of Textual Content and Analytical Guardrails

The textual analysis encompasses the full content of each earnings call transcript, including both prepared management remarks and the subsequent question-answer exchanges with analysts. This decision is explained by the fact that the full range of AI related stories shared in the earnings announcement window will be captured. The disclosure will pose the question of how investors will feel and perceive the information at the moment of disclosure.

Although the previous studies have already established informational differences between prepared remarks and analyst interactions, the current study does not make a distinction between the two parts. This choice is strictly addressed as a delimitation and not an assumption. The research does not give the narrative content to particular speakers, nor does it strive to separate spontaneous and prepared language. These limits are given to maintain the consistency of the analysis done between firms and time and to ensure that the whole story is not lost along the way.

3.4.3 Text Cleaning and Preprocessing Procedures

All transcripts were processed through a standard pipeline to ensure comparability across firms and quarters. Based on the appearance of anomalies and poor data, further steps were necessary. Normalization of text involved turning it to lowercase, eliminating non-alphabetic elements and other junk formatting, and either condensing or eliminating spaces. The boundaries of the sentences were maintained so that they may be used later in the story and the sentiment analysis. The non-substantial information like a timestamp or the name of the person speaking was omitted in the text being analyzed.

Preprocessing decisions were guided by the study's emphasis on transparency and interpretability. Aggressive linguistic transformations, such as stemming or lemmatization, were deliberately avoided to prevent distortion of AI related terminology and to preserve the semantic clarity of domain-specific language. This will make sure that narrative measures can be directly characterized by observed words and phrases in earnings calls.

Apart from textual preprocessing, the selected continuous variables used in the empirical analysis were winsorized to mitigate the influence of extreme observations or outliers. Variables associated with trading volume, volatility and intensity of the narrative were winsorized at standard percentile levels so that they are not sensitive to outliers that can be produced by episodic market shocks or excessively verbose disclosure. This process maintains the statistical rank of the observations as well as minimizing the effects of the outliers and thus improves stabilization and interpretability of the end regression outcomes.

3.4.4 Preparation for Narrative Measurement

After the preprocessing, each transcript was prepared for narrative measurement using the custom lexicon based framework described in subsequent sections. Narrative indicators that based on the text were normalized by the number of words to control the difference in transcript length between firms and quarters. This normalization guarantees that the observed difference in the intensity of AI narratives reflects substantive variation in disclosure emphasis rather than mechanical differences in verbosity.

Every transcript of the earnings calls is a unit of observation that was used in the narrative measurement. So having a clean dataset of transcript was essential. This treatment is in line with the short term effects of the market responses of the study that take place in close time closeness with the announcement of earnings and allows us to directly relate the narrative indicators with the market outcomes.

3.4.5 Data Integrity, Version Control, and Replicability

Finally, transcript files were stored and processed using a consistent directory structure and naming convention to ensure data integrity and reproducibility. All the text prep steps were implemented programmatically to minimize subjective intervention and to allow the analysis to be replicated or extended in future research.

By combining the standardized transcript sourcing and transparent preprocessing procedures, this section establishes a robust foundation for the construction of AI narrative measures. The following section builds directly on this foundation by detailing the development of the custom AI narrative lexicon used to operationalize thematic differences in AI related disclosure.

One observation on the empirical analysis is an earnings call. Since the results are quarterly disclosures of five companies in the 2022-2025 years, the research is designed in such a way that it has about eighty events of earnings calls, which are dependent upon the availability of transcripts and data quality based on the accounting year that each firm follows. The event based sample is such that it offers repeated observations of each firm as time goes by allowing the analysis of the difference in AI narrative intensity and thematic focus without going against the explanatory purposes of the study.

3.5 Development of Custom AI Narrative Lexicon

The key methodological contribution of this research is the creation of a domain-specific, lexicon-based measurement tool that will help to measure artificial intelligence (AI) mentions and their narrations within corporate earnings calls. The proposed lexicon is not only category organized as generic sentiment dictionaries or machine learning classifiers, but also operationally transparent. This part describes the conceptual base, construction, mathematical operationalization and validation structure and documentation plan of the lexicon.

3.5.1 Measurement Philosophy and Rationale

In essence, the lexicon is planned to be a multi-dimensional construct measurement instrument. According to classical measurement theory, a construct is an abstract concept that is not directly observable but must be derived by using indicators that are observable. The constructs like strategic commitment, innovation signaling or uncertainty framing are latent in nature; they are not reflected in observable variable but are reflected in patterns of language (Amundson, 2004).

Measurement theory distinguishes between:

- **Conceptual validity** – whether the construct meaningfully represents the theoretical concept it intends to capture.
- **Operational validity** – whether observable indicators accurately reflect the construct.
- **Structural validity** - whether distinct constructs remain empirically distinguishable

The lexicon is constructed with these principles explicitly in mind.

The current approach views AI narratives as continuous dimensions of emphasis, as opposed to document classification systems, which put text in mutually exclusive thematic categories. Overlapping strategic themes are common in earnings calls: a company can talk about AI innovation breakthroughs, massive capital investment, quantifiable performance improvements, and regulatory uncertainty at the same time. Such a classification model that requires exclusive assignment would distort this communicative reality. Thus, the lexicon is created to quantify the strength of each narrative dimension separately and permit the presence of multiple categories within one transcript.

This design is consistent with strategic signaling theory and narrative economics. Communication associated with AI is not a dichotomous phenomenon. It is a stratified process of disclosure where various strategic functions are implemented simultaneously. Measurement tools should therefore maintain dimensional richness as opposed to reducing content to a unit sentiment polarity measure.

3.5.2 Conceptual Definition of AI Narrative Dimensions

Based on the theoretical framework developed above, AI discussions in the earnings call are broken down into five conceptually independent narrative dimensions:

- **AI Innovation** – it is the language signaling technological advancement, model development, product integration, or research capability expansion.

- **AI Investment** – this references to capital allocation, infrastructure scaling, R&D expenditure, hiring, or resource deployment tied explicitly to AI.

- **AI Performance** – statements that are linking AI initiatives to measurable financial or operational outcomes.

- **AI Uncertainty** – discourse highlighting regulatory risk, execution challenges, technological limitations, or market unpredictability related to AI.

- **AI Ethics and Regulation** – language addressing governance, fairness, compliance, accountability, or responsible AI frameworks.

All categories are theoretically based constructs that depict different strategic signaling functions. These categories are not mutually exclusive; they represent different layers of narratives that can coexist rather than competing for a single label.

3.5.3 Lexicon Construction Procedure

The lexicon was created in a structured, iterative and theory-constrained process aimed to make the lexicon as transparent and replicable as possible.

Stage 1: Construct driven term generation

Rather than starting with frequency based emerging or automated clustering, term identification was informed with predefined construct definitions.

Candidate keywords were determined using:

- Systematic analysis of earnings call transcripts of across firms and timeline as ascertained (2022-2025);
- Determination of AI specific repetitive terms;
- Correlation of words with a single and unique narrative construct.

The inclusion criteria for terms were that they:

1. Explicitly referenced artificial intelligence, machine learning, generative AI, model training, data infrastructure or related areas,
2. Conveyed semantic alignment with the assigned narrative dimension;
3. Appeared across multiple firms or quarters to avoid firm specific idiosyncrasies.

Generic technological terms like “platform”, “benchmark” etc. that were found without AI context were excluded to preserve the purity of the construct.

Stage 2: Ambiguity Screen and Contamination

Candidate terms were screened for:

- Polysemy (the use of multiple meanings in contexts);
- Cross-category overlap;
- Excessive generality;
- Poor instability of occurrence.

Ambiguous and poorly aligned words were eliminated. This inclusion strategy is conservative and does not capture the entire vocabulary exhaustively.

Stage 3: Final Lexicon

The finalized keyword lists for each narrative category have been documented in Appendix B: Custom AI Narrative Lexicon. This appendix includes definitions of all categories, complete keyword lists, inclusion criteria, excluding ambiguous terms and illustrative transcript excerpts. This document ensures that the measurement instrument is fully transparent and can be reproduced. The lexicon is developed through iterative corpus exploration of AI context discourse across earnings calls, allowing category terms to emerge from managerial language rather than being imposed a priori.

3.5.4 Modeling Specification of Transcripts

For standardizing the textual data and analyzing the density of specific AI mentions in each category from the transcripts the model can be mathematically described as below:

For each earnings call transcript i and narrative category c, narrative intensity is calculated as –

$$\mathrm{AI}_{\mathrm{Intensity}_{\mathrm{i,c}}} = \left(\sum_{\mathrm{k} \in \mathrm{c}} \frac{\mathrm{Count}_{\mathrm{i,k}}}{\mathrm{Total}_{\mathrm{Words}_{\mathrm{i}}}} \right) \times 1000$$

Where:

$\mathrm{Count}_{i,k}$ represents occurrences of keyword k

$\mathrm{Total}_{\mathrm{Words}}$ represents total word count of transcript i

The scaling factor standardizes density per 1,000 words

This produces five continuous intensity variables per earnings call transcript.

The operational design ensures key principles:

Dimensional independence: Each category is calculated separately.

Non-exclusive: Multiple categories may register high intensity simultaneously.

Length normalization: Narrative density is comparable across transcripts of varying size.

Replicability: All transformations are implemented programmatically.

This gives us insight into the narrative emphasis of specific categories rather than binary presence alone.

3.5.5 Validation Framework and Measurement Integrity

The lexicon is justified on three levels based on the measurement theory to guarantee that the data is theoretically sound as well as statistically strong:

Conceptual Validity: All the narrative categories are explicitly aligned to known strategic and signaling constructs. This makes sure that the lexicon is gauging theoretically significant dimensions and does not measure arbitrary groups of words

Structural Validity: The internal structure of the data is determined by using:

- **Pairwise correlation matrices** of category intensities.
- **Variance inflation diagnostics** within regression models.

There should be moderate correlation in the areas where themes intersect because of co-occurrences of themes. But a near-unity correlation will indicate construct redundancy, therefore, each category offers distinct information.

Distributional Validity: To ensure data noise is mitigated summary statistics, firm-level means and temporal variation plots are analyzed. The validation criteria includes non-trivial variance across observations, absence of category dominance by a single firm and absence of near-zero categories across most events.

This is the three level validation structure which corresponds to conceptual, structural and distributional layers of measurement reliability. Additional validation is conducted at the empirical modeling stage.

3.5.6 Summary of Empirical Framework

This methodology prioritizes interpretability, transparency and theoretical alignment over algorithmic complexity. This lexicon deliberately does not employ topic modeling, contextual embedding models, dynamic weighting and machine learning classification.

The custom lexicon serves as the main process of transforming qualitative AI discourse into the measurable explanatory variables. These intensity measures include regression inputs to analysis of short term fluctuations in trading volume and implied volatility. The lexicon therefore realizes the conceptual framework in Section 3.1 and gives the empirical basis of hypothesis testing.

3.6 Data Analysis Walkthrough

This study used a multi-stage workflow of data analysis that was structured in a way that provided consistency, transparency, and replicability in all 78 events of the 2022-2025 sample of earnings call events.

Preprocessing of earnings call transcripts of the five selected firms was the first stage. All the transcripts were translated into clean text formats by removing non-informative data such as timestamps, formatting artifacts, as well as non-alphabetic characters. String squishing and lower casing of text were used to remove irregular spacing caused by text. This was done to make sure that the textual information was free to undergo systematic analysis based on lexicon.

After the preprocessing, custom AI narrative lexicon was passed on to each transcript. Each of the five thematic categories, namely AI Optimism, Investment, Uncertainty, Performance, and Ethical AI, had words that were combined into keywords and phrases and each document was matched against keywords and phrases via word boundary regex patterns to avoid false matching. The number of raw mentions of keywords was computed on a transcript level and added to obtain a total AI mentions variable. The normalization of raw counts per 1,000 words to derive a composite AI intensity score also was created to allow the comparison of transcripts of varying length.

Since the variables of counts of AI narratives have skewed distributions, right skew, the right skewed variables were transformed using logarithmic functions q. v. in the form of log(x+1) before the regression estimations. This change explains the decreasing informational effect of repeated mentions of AI and was confirmed by distributional diagnostics such as skewness measurement.

During the third phase, financial market data that was matched by the earnings announcement dates was combined with textual metrics. Change in trading volume was calculated on a day event window of ±1 day that was symmetric, covering anticipatory and instant post announcement responses. The time period implied volatility at the sector level was the NASDAQ-100 Volatility Index (VXN) over a ±2 day window, or the extra time needed for the complex narrative information to percolate the options markets. Each transcript was also analyzed in a sentence-by-sentence mode to come up with a generic sentiment score to use as a comparative measure.

The fourth phase was a regression model in order to measure the connection between the AI narrative measures and the short-term market results. The univariate and multivariate linear regression models were estimated regarding trading volume and VXN volatility. Adjusted R-squared, AIC, and BIC were used as a measure of model fit. Incremental validity test ANOVA was developed to find out whether domain specific AI lexicon had any explanatory power on top of generic sentiment scores. Checks of robustness based on Spearman rank correlation and logistic regression of spikes in volumes were also conducted to confirm results in a different set of specifications.

3.7 Measurement of Variables

This section mentions a summary of the key variables used in the analysis. Each variable is defined very conceptually. It is also described in terms of its operational measurement. The dependent variables capture short term market reactions to the earnings calls. The independent variables reflect the thematic composition of intensity of AI related narratives which are extracted from transcripts. A generic sentiment score is included as a benchmark comparison to evaluate incremental explanatory value of the custom AI lexicon. Table 2 below shows the details:

Table 3.2 Summary of Variables

Variable	**Definition**	**Measurement**
Volume Change	Short-term shift in trading activity surrounding earnings announcement	Percentage change in trading volume over ±1 day event window
VXN Change	Short-term shift in sector-level implied volatility	Percentage change in NASDAQ-100 Volatility Index over ±2 day event window
AI Intensity	Overall density of AI related narrative across the full transcript	Total AI keyword mentions across categories tested and normalized
AI Narrative Categories	Frequency of theme specific language across five dimensions: AI Optimism, Investment, Uncertainty, Performance, and Ethical AI	Raw keyword counts per transcript, with log(x+1) transformation applied where distributional skewness warranted
Sentiment	Generic emotional tone of transcript used as benchmark comparison	Mean sentence-level sentiment score computed using Syuzhet method

Source: Author's own elaboration.

Clean, non-repetitive, and the five categories are acknowledged together without losing any information. The log transformation note is preserved in the measurement column where it matters most.

3.8 Statistical Software and Analytics

The entire data analysis and statistics were carried out in the R statistical processing environment. R was chosen because it has a wide range of text processing, financial data accessing and econometric modeling features. Custom-written scripts were used to analyze earnings call transcripts and identify AI related terminology and assign it to thematic categories using the domain-specific lexicon outlined above.

Trading volume and implied volatility indices were accessed through publicly available financial data interfaces built into the R environment to get market data. Automated procedures were used to compute event-window calculations and percentage change measures in order to obtain consistency in the results across the observations. Simple linear modeling functions were used to estimate regression models and diagnostic tests were conducted to test the assumptions of the model, both the distributional characteristics of the variables and the possibility of the predictors being multicollinear.

All the processes of analysis were modeled to provide results that would be reproducible. Analytical workflow can be reproduced or scaled up in future studies because scripted data processing and statistical estimation can be used.

CHAPTER 4

RESULTS

This chapter summarizes the empirical results of the study of AI related stories in corporate earnings calls and their association with short term market dynamics. The analysis explores the relationship between thematic AI narrative and trading activity and post-earnings volatility using a sample of quarterly earnings call events in five large NASDAQ technology companies in 2022-25. Trading volume change was measured over a three day event window spanning one trading day before to one trading day after the earnings announcement date ([-1, +1]). This window captures anticipatory positioning as well as immediate post-announcement reaction, which is consistent with short term event study conventions in accounting and finance research.

4.1 Descriptive Statistics

The final sample consists of 78 earnings call events spanning five major technology firms between 2022 and 2025. Trading volume and the volatility were carried out using different event windows in order to indicate the different ways of how markets process information in earnings calls. The level of trading attracts immediate interest in the market and liquidity changes after corporate disclosures. In most cases, volume reactions are fast because the earnings calls are usually made after the market is closed and quickly distributed via the financial media and trading platforms. In line with this, the percentage change in the trading volume in the period around the call date that incorporates the adjustment period in the immediate after the markets reopened was measured within a ±1-day window.

Volatility on the other hand is an indication of how the market is changing its evaluation of the risk and uncertainty. Narrative data, especially qualitative descriptions of strategy, technological capability or possible limitations take more time to be interpreted by analysts and institutional investors. Such information is reflected in the repricing of implied volatility in options markets as expected. It is because of this that a marginally broader window of change (± 2 days) was applied to the analysis of changes in sector level implied volatility (VXN). Through this window, there is time to diffuse and interpret the narrative information without projecting to the longer horizons where other market related factors can take over.

The findings are organized in such a way that they first introduce the descriptive properties of the narrative data and then proceed to regression analyses about each of the research hypotheses. The focus of the entire analysis is on market reaction interpretation as a communication strategy and narrative signaling as opposed to strictly predictive modeling.

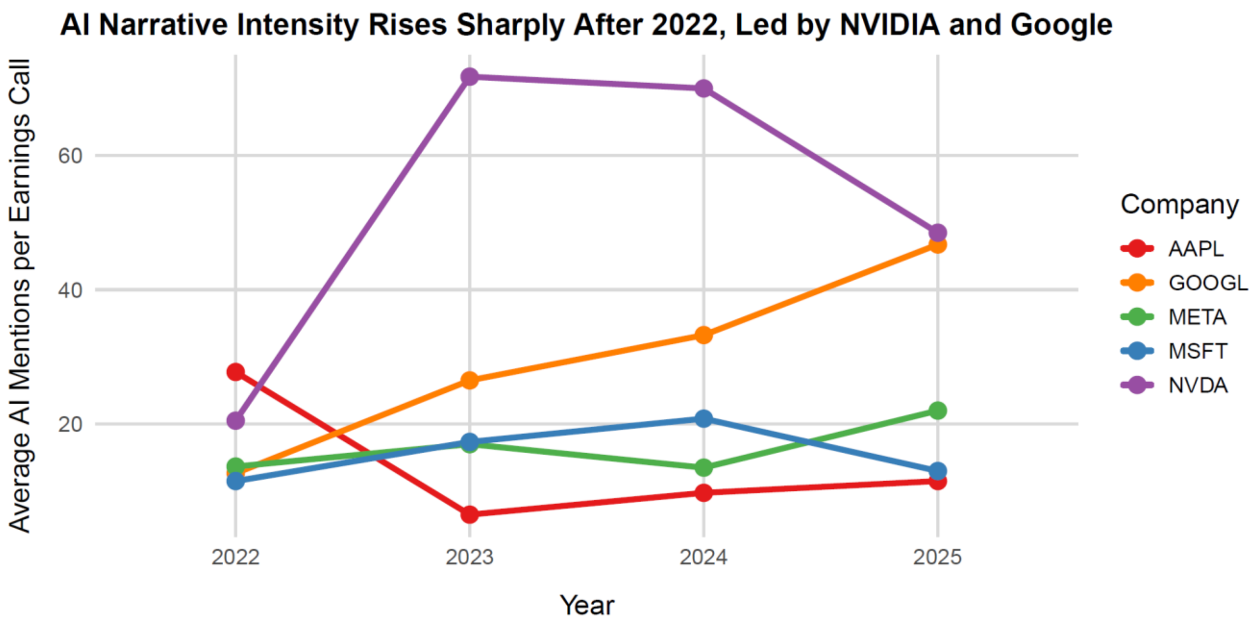
4.2 Model Specification

$$\begin{aligned}\text{Volume Change} \\ &= \beta_0 + \beta_1 \text{AI Intensity} + \beta_2 \text{Optimism} + \beta_3 \text{Investment} + \beta_4\, \text{Uncertainity} \\ &+ \beta_5 \text{Performance} + \beta_6 \text{Ethical AI} + \varepsilon\end{aligned}$$

Where,

AI Intensity captures overall frequency of AI related discussions and, Narrative categories capture thematic composition of AI narratives such as Optimism, Investment, Uncertainty, Performance, and Ethical AI.

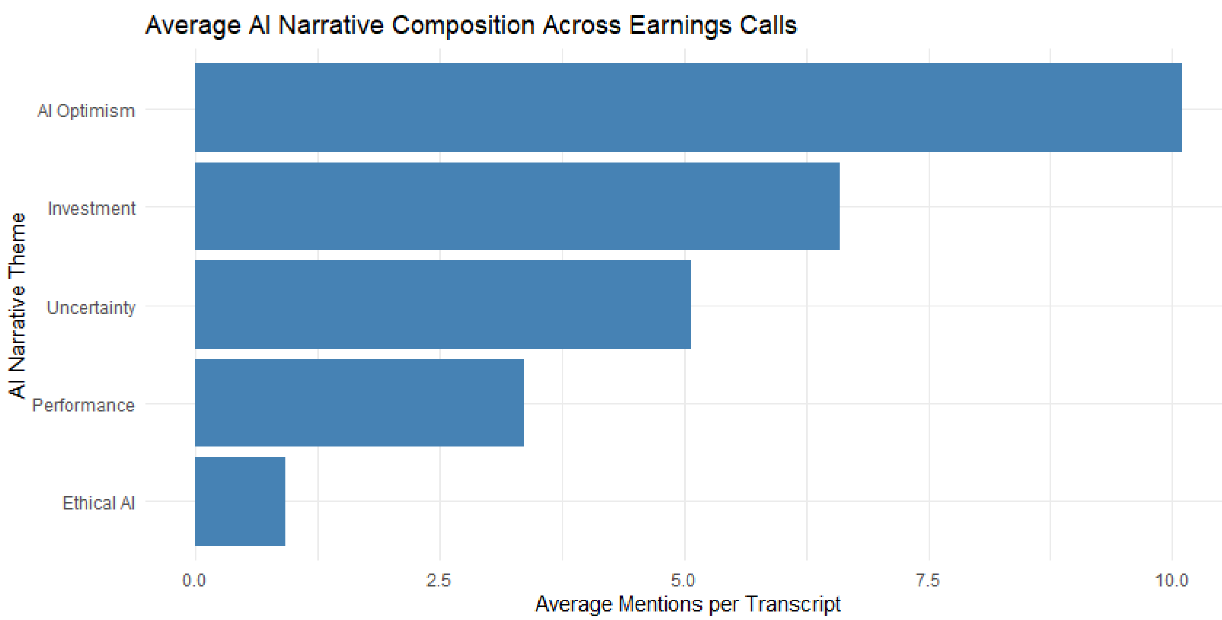
Figure 4.4.1 Evolution of AI Narrative Intensity



Source: Author's own elaboration based on data analysis in RStudio.

The above figure shows the evolution of AI narrative intensity across big tech earnings calls between 2022 and 2025. The results clearly show an increase in AI related mentions or discussions following the emergence of GenAI technologies after 2022. NVIDIA and Google exhibit the most pronounced growth in AI mentions. This is consistent with their focused roles in the AI infrastructure and development of platforms. On the other hand, Microsoft and Apple show more moderate but steady increases in AI narratives intensity. This patten provides a contextual visibility as when AI discourse became an important component of corporate communication during the period of study. This motivated the subsequent analysis of how such narratives influence stock market.

Figure 4.2.2 Average AI Narrative Composition



Source: Author’s own elaboration in RStudio based on data analysis

4.2.1 Linear Models and the Absence of a Monotonic Effect

To evaluate whether AI related narratives influence shrt term market activity, we construct a trading volume reaction measure centered on the earnings announcement date. Consistent with event-study conventions, trading activity is measured over a symmetric three-day window spanning one trading day before and one trading day after the call date (–1 to +1). This window captures potential anticipatory trading, immediate reaction, and short term adjustment effects.

The dependent variable, Volume Change, is defined as:

$$\mathrm{Volume\ Change} = \frac{\mathrm{Vol}_{t+1} - \mathrm{Vol}_{t-1}}{\mathrm{Vol}_{t-1}} \times 100$$

where Vol_{t-1}represents trading volume on the day prior to the call and Vol_{t+1}represents trading volume on the day following the call. This formulation captures the cumulative change in trading activity across the event window and reflects short term shifts in investor engagement surrounding the earnings disclosure.

To test Hypothesis 1: that AI related narratives are associated with elevated short term trading activity - we estimate a series of univariate linear regressions of the form:

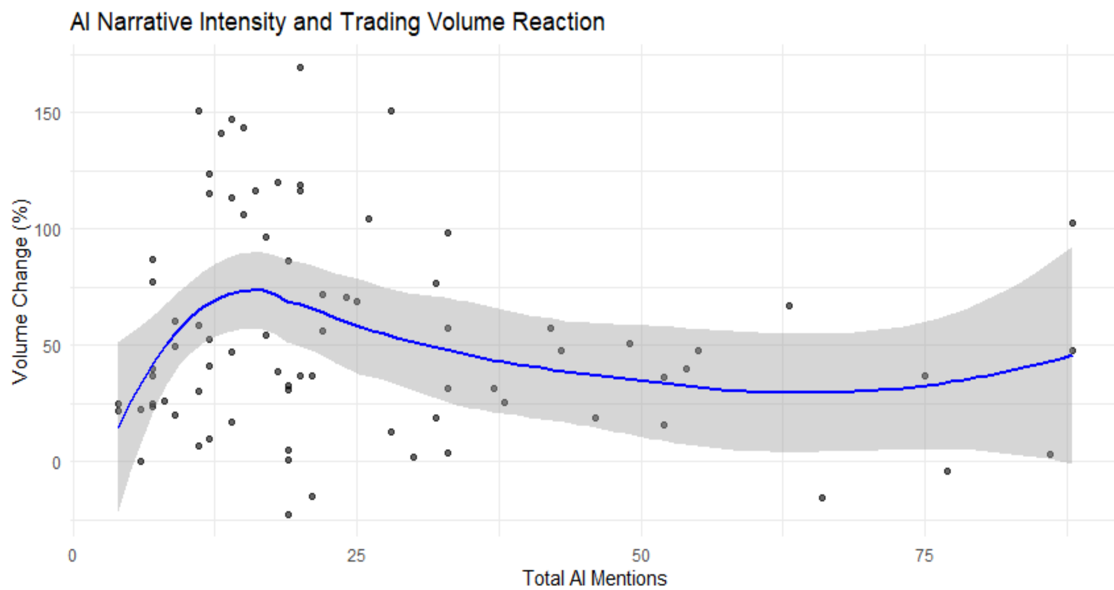
$$\mathrm{VolumeChange}_i = \beta_0 + \beta_1 \mathrm{NarrativeMeasure}_i + \varepsilon_i$$

where NarrativeMeasureincludes total AI mentions (AI intensity) as well as individual thematic categories (optimism, investment, uncertainty, performance). Univariate specifications are employed to avoid multicollinearity between narrative components and to isolate the marginal association of each dimension with trading activity.

4.2.2 Linear Results: Absence of Monotonic Effect

The linear relationship between AI narrative intensity and trading volume is statistically weak. Specifically, the coefficient on AI total mentions is negative and non-significant ($\beta = -0.37$, $p = 0.157$), with a low explanatory power ($R^2 = 0.026$). Similarly, AI optimism ($p = 0.57$), investment (p = 0.32), and performance (p = 0.71) fail to achieve statistical significance. The uncertainty dimension exhibits a negative trend ($\beta = -1.19$, $p = 0.14$), though it does not meet conventional significance thresholds.

Figure 4.2.3 AI Narrative Intensity and Trading Volume



Source: Author's own elaboration in RStudio.

Consistent lack of statistical significance across linear models suggests that market reactions to AI discourse do not follow a simple monotonic structure. Meaning, incremental increases in AI mentions do not produce proportionate increases (or decreases) in trading activity. These results indicate that AI disclosure, at least in aggregate form, does not operate as a straightforward attention amplifier. Rather than interpreting this as a null effect, the pattern suggests that the market response to AI narratives may be structurally non-linear.

4.2.3 Threshold Evidence: The Zone of AI Disclosure

While linear regressions fail to detect a monotonic effect, a threshold-based comparison reveals a statistically meaningful pattern. Earnings calls are partitioned into two groups: those in the top quartile of AI intensity and those in the bottom three quartiles. A Welch two-sample t-test indicates a significant difference in average trading volume between the groups ($t = 2.01$, $p = 0.049$).

On contrary to a simple “more AI equals more trading” hypothesis, the top quartile of AI intensive calls exhibits lower average trading volume (Mean = 40.68) relative to the remaining calls (Mean = 59.55). Confidence interval of the difference, which is 95 percent does not include zero, meaning that this difference is not likely to be randomly observed. This result suggests a non-linear response pattern consistent with information satiation. Moderate levels of AI disclosure may sustain investor engagement, but excessive AI discussion may yield diminishing marginal informational value. Rather than amplifying market participation, extensive AI rhetoric may reflect anticipated strategic positioning, thereby reducing incremental surprise.

Additionally, the negative trend observed in the uncertainty dimension aligns with the concept of ambiguity aversion. Investors may reduce trading activity rather than increase when AI narratives emphasize technological uncertainty, regulatory ambiguity, or strategic risk without resolving these concerns. Ambiguity averse behavior predicts lower participation when outcomes are perceived as poorly defined, which is consistent with the directional evidence observed.

In summary, these findings suggest that AI disclosure operates within a bounded attention framework. There appears to be a "Goldilocks zone" of AI narrative intensity which is sufficient to signal strategic relevance, but not so extensive as to generate narrative fatigue or informational redundancy.

4.2.4 Robustness Checks: Nonlinear and Probability Testing

To ensure that the threshold finding is not an artifact of distributional assumptions, we conduct additional robustness checks:

- Spearman rank correlation between AI intensity and trading volume is non-significant ($\rho = -0.066$, $p = 0.568$), confirming the absence of a monotonic nonlinear relationship.
- Logistic regression predicting extreme volume spikes (top quartile of trading activity) using AI intensity yields non-significant results ($p = 0.208$), suggesting that excessive AI disclosure does not increase the probability of unusually high trading events.

These tests reinforce the interpretation that AI narratives do not uniformly increase short term trading activity but may instead produce attenuated or diminishing marginal effects at high levels of disclosure.

4.2.5 Synthesis: Implications for H1

H1 suggested that AI related narratives would be associated with elevated short term trading volume. The evidence does not support a linear formulation of this hypothesis. However, the significant threshold effect provides qualified support for a conditional interpretation: AI narratives influence trading activity only up to a moderate level of disclosure, beyond which incremental discussion produces diminishing returns. Therefore, H1 is partially supported under a non-linear framework but rejected under a linear specification.

These findings imply that market participants do not mechanically respond to the volume of AI rhetoric. Instead, investor attention appears selective and sensitive to narrative saturation. AI discourse may shape expectations over longer horizons. Or it may influence volatility rather than immediate trading turnover. This is a possibility explored in the subsequent hypothesis.

4.3 AI Narrative of Uncertainty and Volatility

According to the second hypothesis, uncertainty related AI narratives would affect the short term implied volatility after earnings announcements. We start by identifying the difference between systemic and sector level risk. With the VIX, which is an implied volatility of the S&P 500, the correlation between AI uncertainty and volatility was not statistically significant. This is an economically intuitive outcome. VIX is a measure of aggregate macro risk of 500 companies in various industries. The disclosure of AI by five technology companies is not likely to have a strong impact on the economy-wide risk expectations. This reinforces the hypothesis at the macro level. It suggests that AI narratives are currently perceived as sector-specific risks, not systemic macro threats.

Given that case, to align the volatility proxy with the economic exposure of our sample firms, we therefore adopt the VXN - the NASDAQ 100 implied volatility index - the primary dependent variable. Considering the concentration of technology of the NASDAQ, this index is a better indicator of AI associated risk repricing.

This shift in the methodology reflects the market segmentation logic rather than specification searching. It acknowledges the fact that volatility transmission takes place within industries before diffusing to the wider market.

4.3.1 Event Window Identification

Implied volatility is a measure of forward-looking risk expectations embedded in options markets. Narrative disclosures are not quickly absorbed, unlike the case with earnings per share (EPS) surprises. AI strategy discussions, regulatory commentary, and execution risks take time for analyst modeling, institutional digestion, and options repricing.

The ±1 window captures instant repricing in the options market, whereas the ±2 window allows for short term information diffusion and reassessment by the analysts. Given that AI narrative disclosures represent complex strategic communication rather than discrete financial surprises, volatility adjustment may not be instantaneous. The ±1 window captures immediate repricing in the options market, whereas the ±2 window allows for short term information transmission and analyst reassessment. Volatility adjustment might not be immediate since AI narrative disclosures are complicated strategic communication, and not isolated financial surprises. This trend lends itself to the explanation that AI related narrative uncertainty functions in a short diffusion process as opposed to a shock that is completely contemporaneous.

Based on this, we have adopted a ±2 trading day window surrounding the earnings call. This window captures immediate reaction as well as the short term information diffusion. Shorter windows (e.g., ±1) may understate or downplay the adjustment process for complex thematic disclosures. The stronger significance observed in the ±2 specification is therefore consistent with the gradual volatility adjustment rather than model sensitivity.

4.3.2 Model Specification

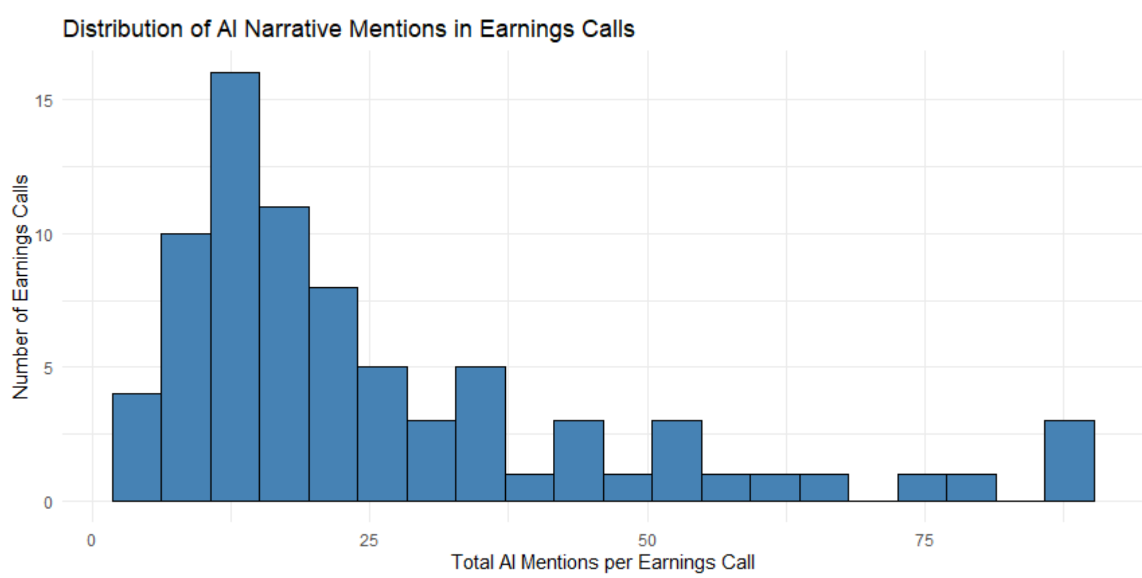
We first estimate a linear specification:

$$\Delta\text{VXN} = \beta_0 + \beta_1\text{Uncertainty} + \varepsilon$$

The coefficient on uncertainty is directionally negative but statistically weak in simple form. The overall explanatory power remains limited. A naïve “more uncertainty words = more volatility” model does not adequately describe market behavior.

This finding is theoretically meaningful. It suggests that volatility responses to AI narratives are not linear in magnitude. Investors do not respond proportionally to raw counts of uncertainty mentions.

Figure 4.3 Distribution of AI Mentions



Source: Author’s own elaboration in RStudio based on data analysis.

The distribution of AI narrative counts is right skewed (skewness = 1.48). This implies that a small number of calls contain very high mention counts, while most observations cluster at lower levels.

In terms of the impact, the informational difference between 1 to 5 uncertainty mentions is substantially larger than 80 to 85 mentions. In other words, narrative impact likely exhibits diminishing marginal sensitivity. This justifies the need for a logarithmic transformation.

We therefore estimate:

$$\Delta \mathrm{VXN} = \beta_0 + \beta_1 \log(1 + \mathrm{Uncertainty}) + \varepsilon$$

The results are statistically significant:

- β (log uncertainty) = −3.155
- $p = 0.020$
- $R^2 \approx 0.069$
- Adjusted $R^2 \approx 0.057$
- Residual variance declines meaningfully
- VIF values < 2 (no multicollinearity concern)

This model uncovers a robust sector-level effect that was obscured in the linear specification.

4.3.3 Interpretation: Ambiguity Aversion and Risk Clarification

The negative coefficient shows that higher proportional increases in uncertainty related AI narratives are associated with decreases in the implied volatility.
At first glance, this appears counterintuitive. However, behavioral finance offers a compelling explanation: ambiguity aversion. Markets fear ‘unknown’ uncertainty more than ‘disclosed’ or pre-established uncertainty.

By stating the AI related risks explicitly - regulatory exposure, implementation challenges, execution complexity, the management minimizes the informational ambiguity. Organized recognition of uncertainty signals is an indicator of transparency and strategic awareness. As a result, implied volatility declines. In contrast, clarity stabilizes expectations.

This reframes H2. The AI uncertainty does not increase volatility through alarm; it reduces volatility through by bringing clarity. The contrast between VXN (significant) and VIX (insignificant) forms an important structural conclusion:

AI narratives currently represent idiosyncratic technology sector risk, not systemic macro risk. This is a key segmentation insight that contributes to the thesis. It shows that the discourse of AI influences the risk pricing of concentrated innovation sectors, then spreads to wider markets.

4.3.4 Sector Volatility and Discovery

The results of the volatility analysis indicate that there is an organized and economically meaningful pattern. The details of uncertainty that comes with AI do not inherit to systemic market risk: there is no big deal in the specification of VIX. Instead, volatility responses are suggested in the technology sector and can only be achieved through the incorporation of the NASDAQ 100 implied volatility index (VXN) as the dependent variable. Moreover, the relationship is statistically observed after distributional skewness and decreasing marginal informational influence is corrected with the help of the logarithmic transformation.

The data indicates that AI uncertainty is not a destabilizing shock but is a clarifying mechanism. By having the management explicitly state risks, ambiguity is minimized, and implied volatility at a sector level decreases. This is a positive trend towards a behavioral explanation in terms of the aversion to ambiguity in the sense that markets respond more adversely to opaque stories than to structured disclosures of risk. Collectively, these results suggest that AI narratives have become a reflection of sector-specific technological risk rather than macroeconomic instability and narrative volatility is a response to proportional narrative intensity, and not the frequency of mentions. This qualifies the following step of investigation, which is whether domain-specific AI narrative measurement has explanatory power over and above generic sentiment models.

4.4 Domain Specific AI Lexicon

Hypothesis 3 proposed that a domain specific AI lexicon would provide better explanatory value to understand sector-level market volatility compared to a generic sentiment based model. Unlike H1 and H2, which explored whether AI narratives influence trading activity and volatility, H3 evaluates the quality of measurement itself. The central question is not whether AI narratives are important, but whether a structured, context sensitive AI lexicon or AI vocabulary captures market-relevant information more effectively than broad sentiment polarity.

To ensure comparability across models, VXN percentage change (Nasdaq-100 implied volatility, ±2-day window) was considered as the dependent variable. Model comparison relied on adjusted R^2, AIC, BIC, and incremental F-tests to determine whether informational improvements reflected genuine informational gains rather than increased parameterization.

4.4.1 Distributional Diagnostics and Model Specification

Distributional diagnostics were performed before estimation in order to have valid functional form. With AI total mentions, skewness was significantly positive (skew = 1.48), which is indicative of a right skewed distribution that was similar to a decreasing marginal informational utility. This means in the context of narrative disclosure that the difference in 2 and 5 mentions may be informationally relevant whereas the difference in 50 and 55 mentions may not be proportionally increasing market impact. To stabilize this variance and reflect nonlinear effects, a log(1+x) transformation of thematic AI variables was applied.

Conversely, the generic sentiment measure had low skewness (0.44) which implies that it is more or less symmetric and therefore warrants a linear specification. This difference is indicative of a classical conceptual difference: the degree of narrative accrual is nonlinear because of information saturation, and sentiment polarity is a finite and scale is a normalized concept.

The ±2 day VXN window was retained to capture the information diffusion at the sector level, as thematic AI disclosures are complex ‘soft information’, which takes time to be interpreted by the institution and price options

4.4.2 Generic Sentiment Model

The baseline model regressed VXN change on generic sentiment alone. The model explained only 2.1% of variation in implied volatility (adjusted $R^2 = 0.021$), and the coefficient was statistically insignificant ($p = 0.106$). While the sentiment coefficient was positive, suggesting that more positive tone may be associated with volatility increases, the relationship lacked statistical reliability.

This explanatory value was strengthened by model selection criteria. The Akaike Information Criterion (AIC), which evaluates model fit while penalizing unnecessary complexity, yielded a value of 562.83. Lower AIC values are an indication that there is a good balance between the explanatory power and the parsimony. In the baseline case, the generic sentiment did not give a lot of volatility information. These results indicate that extensive emotional tone is not a significant contributor to sector level volatility movement in AI related earnings disclosures.

4.4.3 AI Intensity Model

The AI intensity model employed log-transformed total AI mentions as the sole explanatory variable. This specification significantly improved the explanatory power compared to sentiment (adjusted $R^2 = 0.026$; $p = 0.083$) but it was statistically very marginal. The negative coefficient suggests that higher AI narrative concentration may be associated with volatility contraction; however, the outcome did not attain a standard statistical significance. The intensity model marginally minimized the AIC compared to the sentiment model (562.42 vs 563), but the margin was not significant and failed to satisfactorily determine the structured informational content in thematic AI disclosures. Raw narrative volume even in the form of a log-transform does not seem to provide sufficient information to account for the volatility dynamics.

4.4.4 AI Thematic Model (Log-Transformed)

The log-transformed AI thematic specification produced a substantial improvement in explanatory performance. The model was statistically significant at the joint level (F-test $p = 0.0229$), and adjusted R^2 increased to 0.095, representing more than a fourfold improvement relative to the sentiment model. The AIC declined to 559.56, the lowest among all competing specifications, confirming superior statistical fit even after penalizing additional parameters.

Most importantly, log_uncertainty appeared as highly significant ($\beta = -4.76$, $p = 0.0018$). The negative coefficient implies that structured AI uncertainty disclosures are related to drops in Nasdaq-100 implied volatility. This finding similarly matches the ambiguity aversion theory:

opaque uncertainty is met with a worse response in markets than transparent risk. When firms acknowledge AI related constraints such as compute limitations, regulatory exposure, or deployment risks they reduce ambiguity rather than amplifying fear. From a microstructure perspective, explicit disclosure of uncertainty reduces information asymmetry, thus narrowing option-implied risk premiums. Instead of causing panic, structured risk acceptance seems to stabilize volatility.

4.4.5 Incremental Validity and Measurement Dominance

To test measurement superiority directly, an incremental model incorporating both generic sentiment and AI thematic variables was estimated. In this joint specification, log_uncertainty remained highly significant ($p = 0.0086$), while generic sentiment became statistically irrelevant ($p = 0.248$). This indicates that once structured AI themes are accounted for, sentiment does not provide any additional explanatory power.

An ANOVA comparison between the sentiment-only model and the incremental model proved that the addition of AI thematic variables significantly improved the model fit ($F = 2.65$, $p = 0.039$). This establishes incremental validity: the AI lexicon has distinct informational information that cannot be described using generic tone values.

In practical terms, this reflects improvement in signal-to-noise ratio. In statistical modeling, ‘signal’ refers to systematic variation explained by predictors, while ‘noise’ refers to random or irrelevant variation. Best generic sentiment reflects the general emotion tone that can have a lot of noise in technically specific situations. By filtering domain specific constructs e.g. uncertainty, investment and execution framing AI lexicon can serve as a strategic filter. It improves the accuracy of information because it eliminates the irrelevant emotional variation and isolates structured information that institutional investors view as economically significant.

4.4.6 Theoretical Contribution: Semantic Decay and Domain Specificity

These findings contribute to the literature on corporate communication and market microstructure as they indicate the weaknesses of the 'time agnostic' sentiment models in the context of new technological fields. Generic sentiment dictionaries are constructed from historical corpora and capture broad emotional valence. Nevertheless, they are not sensitive to domain specific terminologies which change with the changes in technology. This process may be termed semantic decay: when the language is redirected to special strategic content, the broad polarity measures become no longer explanatory.

The AI lexicon that has been developed within this thesis is time conscious and context sensitive. It cures the technical jargon of the existing innovation cycle such as compute scaling, regulatory control, deployment restrictions, and performance assembly.

The generic sentiment is found to be more directly related to the volume of short term trading, and the structured thematic variables become more significant to the sector volatility causes. These results do not mean that market response can be segmented in general in relation to different informational characteristics of corporate discourse, but rather that various dimensions of market response might depend on varying informational characteristics of corporate discourse. The tonal polarity in this dataset is more associated with trading activity, whereas structured uncertainty is more associated with implied volatility. Based on the large rise in explanatory power, significant incremental validity and increase in information criteria, the Hypothesis 3 is strongly supported (Volatility Domain).

These results are methodologically useful as they show that domain based narrative measurement can enhance explanatory performance compared to generic sentiment models in some market situations. The findings suggest that structured AI disclosures carry information that can be used to explain sector-level volatility which cannot be measured using general tonal polarity indicators. To practitioners, this implies that the manner in which firms explain uncertainty and strategy can have an impact on the way markets make sense of technological changes, especially in concentrated industries like large-cap technology.

4.5 Synthesized Research Conclusions

The results in three hypotheses indicate that AI associated with corporate narratives have multiple informational effects on financial markets, but not in a single homogenous manner. The simple linear relationship between the volume of AI discussion and market reaction is not supported by the results. Rather, they demonstrate nonlinear, threshold-based, and context-dependent effects, which differ in dimensions of the market.

In regard to trading activity (H1) markets seem to be sensitive to narrative salience and not incremental AI discussion growth. The threshold analysis shows that disclosure of AI at very high levels is found to be related to less further trading volume, indicating diminishing marginal informational effects or perhaps “hype fatigue”. Linear models did not detect consistent effects, reinforcing the idea that investor response is not proportional to quantity of the narrative. Trading volume, therefore, seems to indicate an attention-based mechanism where broad tonal cues and narrative intensity does indeed influence short term engagement, but not in a continuous pattern.

The volatility results (H2) introduced a distinct dynamic. AI related uncertainty, with the uncertainty metric being empirically measured with a structured thematic lexicon, and fitted with a suitable nonlinear transformation, explains Nasdaq-100 implied volatility across a ±2-day window. Notably, the same effect is not applicable to the larger VIX index, which means that AI discourse is rather sector-specific than systemic information. The co-relationship between structured uncertainty and implied volatility is negative, indicating that explicit recognition of technological risk can potentially decrease ambiguity as opposed to increasing market fear. This interpretation aligns with ambiguity aversion theory: markets may react more cautiously to unarticulated uncertainty than to perceived risk.

AI lexicon superiority (H3) further extends these insights by evaluating measurement quality. Although generic sentiment measures are practical in explaining the magnitude of trading, they have little explanatory power regarding the volatility of the sector. In comparison, domain specific AI lexicon is much better in terms of model fit and explanatory power that remains even during sentiment control. Incremental validity test proves that the structured thematic variables have informational content that is not contained by tonal polarity. This does not mean that sentiment is not relevant, but simply that the informational characteristics that are used in the case of volatility repricing are not the same as the informational characteristics used in the case of trading activity.

Combined with the results, these findings indicate the presence of a stratified model of narrative transmission. AI discourse appears to affect markets along at least two dimensions: an attention channel or tone and salience, and a volatility channel or structured uncertainty disclosure. These channels are different and react in different ways to the features of the narrative structure and are nonlinear. The results thus warn against the use of generic sentiment analysis in the assessment of the emerging technological disclosures.

On a larger scale, the paper shows the significance of domain specificity in textual measurement. Since communication in corporations already involves the use of technical and strategic terms connected to the field of artificial intelligence, the traditional methods of polarity might be able to reflect only a part of the information world. Thematic frameworks can be structured to offer further descriptive data, especially in sectors that are tech focused. These findings form the background of the final chapter which explains theoretical implications, methodological contributions, managerial relevance, and future research directions.

CHAPTER 5

DISCUSSIONS, CONCLUSIONS AND FUTURE RESEARCH

5.1 Overview of this research

Chapter 5 gives a detailed discussion of the background of this study, bringing together the empirical findings, theoretical background and the practical implications. This chapter is meant to explain the implications on Chapter 4 findings given the research questions and hypotheses of Chapter 1 and the theoretical and empirical literature surveyed in Chapter 2. Where the former chapter was devoted to the presentation of the statistical findings and the graphs of the empirical data, the current chapter offers a more comprehensive interpretation of the findings and explores their implications on the academic research, professional practice, and future investigation. In this manner, the chapter integrates the analytical findings of the research and places them in the context of the wider discussion of corporate discourse, technological innovation, and the dynamics of the financial market.

The key aim of the study was to explore the impact of artificial intelligence (AI) narrative disclosed in corporate earnings calls on financial market performance. The last ten years have been marked by the emergence of technological innovation, and especially, the aspect of artificial intelligence as a means of corporate strategy in the world of major technological companies. Firms are beginning to use narrative discourse to inform investors about their technological solutions, strategic investment, and future aspirations, in earnings calls and other forms of communication to the investor. These stories tend to go farther than the conventional financial reporting and rather contextualize the wider technological vision, competition and innovation path. Accordingly, the earnings calls have become a significant avenue whereby corporate executives decipher the new technological trends on behalf of the investors and analysts.

In this sense, corporate stories can be seen as interpretive communication whereby companies describe complicated changes to investors. The narrative aspect of corporate communication is of particular importance when the newly developed technologies like artificial intelligence gain strategic importance. Some of the common AI strategies include long development cycles, unpredictable regulatory measures, and changing technology abilities. Consequently, AI investments might not have an immediate impact on numerical financial statements to indicate the strategic implications. Earnings call scripts are thus a process whereby corporate leaders make sense of changes in technology and convey anticipations regarding future events.

Although the role of technological narratives in corporate communication has increasingly become significant, there have been very little empirical studies that have investigated the effects of technological narratives on financial markets in a systematic manner. Much of the literature that has been developed so far on textual analysis in finance is based on generic sentiment dictionaries which detect positive or negative tone in corporate disclosures. Although such methods have served well in establishing broad emotional cues in the context of corporate communication, it may not be effective in circumstances where the domain specific language is related to new technologies. Arguments related to artificial intelligence, such as the ones in this context, often mention technical performance, investments in infrastructure, regulatory factors, and product usage. Such factors might not be sufficiently represented by the traditional measures of sentiment, which were initially formulated on the basis of general textual corpora in opposition to specialized technological discourse.

Linguistic analysis offers an organized way of drawing out and measuring these narrative cues. The development of natural language processing and computational text analysis has enabled the analysis of large amounts of unstructured corporate communication in a manner that was previously impossible. Through the identification of common themes, linguistic patterns and narrative forms, linguistic researchers can convert qualitative textual data into quantifiable variables which can be analyzed with financial market data. This research method gives researchers the chance to explore the impact of narrative framing on the perceptions of investors and the response to the market.

The linguistic analysis is especially applicable in the case of artificial intelligence since the technological discourse is usually characterized by the use of specialized vocabulary and thematic structures which are significantly different than the traditional financial communication. The discourse of AI might include mentions of models capabilities, compute infrastructure, regulatory, data governance, or even ethics. The analytical tools needed to capture these themes must be domain-specific to identify language that are related to concrete domains, as opposed to using general sentiment indicators. The emergence of an AI oriented narrative lexicon thus constitutes an effort to more accurately mirror the structure and the informational content of a technological discourse in corporate earnings calls.

These forces can be seen as constraints of generic sentiment analysis. The explosive emergence of AI as a strategic corporate focus, the unprecedented investment in AI infrastructure and the enhanced awareness of narrative information in financial markets, together provide the impetus to the current study. By analyzing the appearance of AI related narratives in earnings call transcripts as well as their associated effects on the performance of financial markets, this study will contribute to the better comprehension of the impact of new technologies on corporate communication and investor behavior.

The rest of this chapter expands on these findings by discussing their wider implications. Section 5.2 offers the overall summarization of the study and its empirical findings, with the findings being directly related to the research questions and hypotheses that were set out previously in the dissertation. In Section 5.3, conclusions of the study are provided summarizing the empirical data and explaining the impact of the findings on the current body of knowledge on corporate narratives and financial markets. Then Section 5.4 explores the implications of these findings for professional practice which includes some recommendations for corporate executives, investors, and policymakers. Finally, Section 5.5 addresses the limitations of this study and outlines several directions for future research that could build upon the analytical framework developed in this dissertation. Together, these sections provide a comprehensive reflection on the significance of the research and its contribution to understanding the evolving landscape of technological narratives in financial markets.

5.2 Summary and Key Findings

This chapter provides a summary of the design of the study and a review of the empirical findings published in Chapter 4. This section is meant to summarize the findings of the analysis and provide them in a logical story that is representative of the structure presented in the research questions and hypotheses discussed in this dissertation. Although Chapter 4 described the statistical models and findings in some detail, the current section summarizes such findings to understand the key empirical patterns in the data and see how they relate to the study objectives.

This framework is based on the analysis of transcripts of earnings calls of a sample of large technology companies (including Apple, Microsoft, Google, Meta, and NVIDIA) which is based on the use of lexicon. These companies are the most active players in the entire world AI ecosystem and altogether occupy the most important place in the technological innovation of the digital economy. This sample only included the earnings calls that occurred between 2022 and 2025; the period when the field of generative AI technologies rapidly evolved and the interest in artificial intelligence started to grow among the population and investors in general. With help of the analysis of the patterns of narrative in this timeframe, the research was trying to capture the shift in the form of corporate communication to AI as the technology started to take strategic weight.

To fill this gap, the current research project came up with a domain specific analytical model that aimed at capturing the thematic organization of AI related reports in corporate earnings calls. Based on the findings of the literature regarding corporate communication, reaction of the financial market and technological innovation, the study created a tailor-made AI narrative lexicon, which includes five topical categories: **AI optimism, investment, uncertainty, performance, and ethical AI**. Each category represents a particular aspect of the communication that firms do about artificial intelligence. AI optimism reflects the words linked to technological discoveries and prospects of the future. Investment shows conversations of capital and infrastructural set-ups with regards to AI capabilities. Uncertainty involves allusions to risks, regulatory factors, and unaddressed technology. Performance documents statements about the adoption, implementation, and monetization of AI technologies. Ethical AI is indicative of debates within the governance, responsible development and the social implications of artificial intelligence.

The study first investigated the descriptive data of the dataset before testing the hypothesis. The descriptive analysis indicated that the discussion of AI became more pronounced in the earnings calls over the course of the sample. The number of mentions of AI increased significantly in 2022-2025, which means that artificial intelligence turned out to be a dominant theme in corporate communication in the given period. Such a rise in narrative intensity is in line with more general changes in the technology sector, with AI taking on an even larger role in corporate strategy and innovation efforts. The descriptive analysis additionally demonstrated the differences in AI narrative intensity across firms which were a result of differences in technological orientation and strategic positioning in AI ecosystem.

There were three main research questions that were studied empirically. First, the paper was investigating whether the presence of AI related discussion in the earnings calls affects investor attention as measured in abnormal trading volume during earnings announcements. Second, the paper examined the presence of particular thematic elements of AI stories in terms of their impact on sector volatility in the technology market through the lens of Nasdaq-100 Volatility Index (VXN) changes. Third, the authors tested the hypothesis that a domain-specific AI narrative lexicon can be more effective in the prediction of market responses than standard textual analysis approaches that rely on sentiments.

The study used a mixture of textual analysis methods with financial market information to answer these questions. The custom lexicon was used to determine AI narrative intensity and thematic composition on transcripts of earnings calls. The trading volume and volatility measures of the event-window around earnings announcements were used to capture the market reactions. The relationships between narrative variables and market outcomes were then evaluated using regression models. Models using the AI lexicon were also compared to models using generic sentiment measures in the analysis to determine incremental informational value of domain specific narrative analysis.

The initial research question was whether the strength of AI related conversations in the earnings calls is correlated to investor attention changes. Changes in trading volume of earnings announcements were used to operationalize investor attention. The empirical research examined the hypothesis that the higher the amount of AI related discussion on the earnings call, the higher the trading activity during the event window evaluated. The findings provided in Chapter 4 show that trading volume reactions are positively correlated with AI narrative intensity. The higher the proportion of AI related discussion in the earnings calls, the more likely it was that the period would coincide with an increased trading activity. This observation indicates that investors are keen on following news surrounding the subject of artificial intelligence and use the data in their decision-making process. In that regard, the stories of AI seem to serve as indicators that help draw investors and create a market buzz when earnings are announced.

The second research question was to analyze the impact of the thematic form of AI narratives on volatility in the technology industry. Sector volatility was calculated by using fluctuation of Nasdaq-100 Volatility Index (VXN), which is an indicator of anticipated volatility of the Nasdaq-100 index. A specific part of the analysis was given to the whether narratives that highlight technological uncertainty (e.g. mentioning regulatory changes, technological risks, or unresolved issues) are connected to volatility reactions. The empirical findings are that the narratives, which are driven by uncertainty, are significantly connected to the shifts in sector volatility. Those earnings calls in which the uncertainty about AI technologies was more discussed were related to quantifiable changes in the VXN index. This observation is a pointer that investors perceive technological risk and uncertainty talk as information that cuts across the board market expectations in the technology industry.

The third of the research objectives evaluated whether a domain-specific AI narrative lexicon can explain market reactions by a stronger insight than the traditional textual analysis based on sentiment analysis. The research answered this question by comparing models using the thematic AI narrative variables to models using generic sentiment scores using typical textual analysis methods. The findings demonstrate that the domain specific AI lexicon has better explanatory predictive abilities in volatility outcomes compared to models that only focus on generic sentiment. Although sentiment measures reflect the general mood of managerial communication, they are unable to distinguish between different kinds of technological narratives. In comparison, the AI lexicon determines particular themes connected to the opportunity of technologies, investment commitment, and uncertainty and thus represents a more detailed portrayal of the information revealed in the stories of earnings calls.

The combined results indicate that AI stories have become a significant informational element of corporate communication in the technological industry. The growth in the number of AI related discussion during earnings calls suggests that companies are allocating more resources to discussing their AI based strategies with investors. These empirical findings further indicate that these stories are not just a commentary rather they might have information that investors could use in their decision making processes. The movement of higher trading after AI intensive earnings calls shows that investors are sensitive to these types of narratives, and the correlation between uncertainty and volatility narrative implies that technological risk discussion affects future market expectations.

Overall, the findings of this paper indicate that the analysis of the thematic content of technological discourse can offer some insightful information on the interaction between corporate communication and financial market movements. The research proposes a methodological framework in the analysis of the discussion of emerging technologies through corporate disclosures, and the relationship between such discussions and observable market outcomes by developing and implementing a domain-specific AI narrative lexicon. The next part expands these results, the larger conclusions of the study, and explains their meanings in the context of the research questions already defined at the beginning of this dissertation.

5.3 Conclusions from this Research

The empirical investigation carried out as part of this study demonstrates a differentiated and structured pattern of the relationship between artificial intelligence (AI) narratives and the behavior of financial markets. Instead of having the same level of influence, AI related disclosure seems to act in different ways that have a non-linear and context-specific effect on the various dimensions of market outcomes. The data has been consistent with a multi-channel explanation where the narrative structuring, thematic composition, and intensity of disclosure together affect investor reactions, however, this effect varies based on the outcome being studied and the method used to detect the outcome. This distinction can be more clearly seen through comparing attention based responses with risk based responses, which have different statistics and behavioral traits.

The first channel is based on the dynamics of limited attention, i.e. the interdependence between AI narrative strength and the trading activity is more of a non-linear threshold structure than a mere monotonic process. The AI intensity showed a negative but not a very significant coefficient ($\beta = -0.37$, $p = 0.157$), and the thematic categories such as optimism ($p = 0.57$), investment ($p = 0.32$), and performance ($p = 0.71$) also did not reach statistical significance.

These results indicate that the connection between AI narratives and investor attention cannot be effectively captured in a linear formulation.

A threshold based analysis however shows there is a smoother structure. Once the earnings calls are divided between high AI intensity (top quartile), and moderate-to-low intensity (bottom three quartiles) a statistically significant pattern is observed. The average trading volume (Mean = 40.68) of the calls in the top quartile is lower as compared to the other calls (Mean = 59.55), which are statistically significant ($t = 2.01$, $p = 0.049$). This negative correlation indicates that the best level of AI disclosure intensity does exists. Moderate levels of AI discussion appear sufficient to signal strategic relevance and capture investor attention. Whereas, excessive discussion in the earnings call may generate diminishing marginal informational value.

This trend follows traditional findings of the attention theory and behavioral finance. The AI related discourse transcended into more earnings calls, especially during the study period (2022-2025), after the blistering growth in commercialization of the generative AI and other investments in data center infrastructure and compute capacity. Under such a condition of narrative saturation, it seems that investors distinguish the more substantive strategic communication and more generic or repeat references. Moderate AI disclosure acts as an attention cue. However, when repeated on a large scale, it can decrease the informational novelty and the strength of trading reactions.

The uncertainty aspect gives more insight into these attention dynamics. Although not significant in linear models, the uncertainty-related narratives have a steady negative directional correlation with the volume of trading ($\beta = -1.19$, $p = 0.14$). This trend is in line with ambiguity aversion, whereby investors are more inclined to well defined risks rather than uncertain, or imprecisely defined outcomes. Investors can delay trading instead of attending to AI related issues when companies highlight the problems but fail to offer clear-cut solutions that direct the process, for example, navigating regulatory uncertainty, dealing with technology constraints, or overcoming operational risks. In this regard, a high degree of uncertainty can have a role in decreased short term trade.

Collectively, the evidence indicates that the correlation between AI narratives and trading action is non-linear and threshold effects influence it. Investor attention does not go hand-in-hand with the amount of communication regarding AI related information but rather indicates selective processing, which is predetermined by the informational clarity and novelty. This is a refinement of the hypothesized premise by suggesting that the intensity of narrative does count, but within limited cognitive boundaries.

A second mechanism is based on risk perception where thematic content, especially uncertainty, is associated with sector-level volatility expectations. Early specifications that investigate the connection between AI uncertainty and the overall market volatility (VIX) show non-significant results, meaning that AI related disclosures do not seem to have an impact on the perception of risk on an economy-wide basis. This is in line with the composition of the VIX that is a aggregate expectation across a wide array of industries.

Understanding this sectoral peculiarity, the analysis then targeted the Nasdaq-100 Volatility Index (VXN) that better reflects the dynamics of the technology sector which is concentrated to our scope. To counter the gradual influx of complex narrative information towards market expectations, the event window was lengthened to ± 2 days. The rationale of this change is economic: The volatility reactions to the qualitative disclosures tend to appear on longer horizons than at the disclosures of the discrete financial surprises. Financial surprises can be estimated early by "plugging the numbers", while technological impacts need to be assessed by the information technology team in the qualitative context.

The methodological refinement was also necessary due to the distribution of the AI narrative variables. The uncertainty variable exhibited right skewness (1.48) which indicated that a small number of observations contained disproportionately high mentions of AI. This trend indicates that informational impacts are also decreasing, and subsequent mentions on high levels provide less incremental information than initial disclosures. To address this non-linearity, a logarithmic change was implemented to the data.

With a logarithmic transformation, the relationship between uncertainty and VXN becomes statistically significant ($\beta = -3.155$, $p = 0.02$). Further, the model accounts for 6.9% of variation in volatility of trading. The negative coefficient indicates that the more uncertainty is discussed on a call, the lower the implied volatility of the stock. An example of thematic risk clarification can be used to explain this finding. So, in the event that the management clearly identifies AI related risks like regulatory exposure, infrastructure bottlenecks, or implementation issues – these disclosures can lead to a decreased level of informational ambiguity. Firms convert the uncertain or opaque risks into a structured and identifiable risk perception which allows the investors to better integrate those risks into their expectations.

This is consistent with the behavioral finance findings which indicate that markets react more to ambiguous uncertainty than risk, which is clearly understood. Transparent acknowledgment of uncertainty may therefore stabilize expectations rather than amplify volatility. The fact that the same effect cannot be observed in VIX also contributes to the conclusion that nowadays the dynamics are also trapped in the technology industry, where AI related risks are the most directly applicable and expected.

The third aspect of the analysis measures the quality of measurements through the comparison of domain specific AI narrative variables with generic sentiment measures. These findings reveal that the volatility results can be explained based on sentiment models with only a small share of variance with the failure to become statistically significant. Sentiment is a more general tone, which fails to distinguish different informational dimensions that are embedded in technological stories.

The thematic AI model, on the other hand, exhibits better explanatory performance. When log-transformed narrative categories are included, model fit is improved, adjusted R^2 increases to 0.095 and model selection criteria show improved performance compared to sentiment based specifications. In this context, uncertainty can be seen as a statistically significant predictor, and the other thematic dimensions can be seen as an addition to the overall explanatory structure.

The incremental value of the domain specific lexicon is verified further through further analysis. In the case of the joint presence of the sentiment and thematic variables, the uncertainty variable will remain statistically significant and the sentiment one will be non-significant. This shows that the AI lexicon is able to capture informational data that is not captured using generic sentiment measures. As the results suggest, the narratives of technology are inevitably multidimensional and have many aspects of opportunity, investment, and risk, which cannot be effectively estimated by a single score based on polarity.

Taken together, these results facilitate a hierarchic approach to narrative influence. AI disclosures seem to have a variety of channels, which touch on markets: an attention channel, with threshold dynamics and cognitive filtering, and a risk perception channel, with structured updating of expectations. These channels are active at the same time but affect various elements of investor behavior. Overall, the paper shows that AI related textual representations in corporate earnings calls lead to quantifiable market results using unique and conditional processes. The occurrence of non-linear effects of attention, industry specific risk clarification dynamics, and the significance of domain specific measurement all implies that technological stories are an informational dimension worth drawing attention in financial markets.

5.4 Implications for Practice and Future Research

The outcome of this research has significant implications on corporate communication practice, investment analysis, and the overall knowledge on the application of emerging technologies, especially artificial intelligence, to the context of financial decision making. With the current shift of AI as an experimental feature to a business strategy, the manner in which companies share their AI efforts is becoming more consequential day by day. The findings indicate that these messages are not purely descriptive, but markets interpret them as a constituent of informational environment in terms of both attention and risk assessment.

Regarding the corporate communication point of view, it has been shown that the design and weight of AI related disclosures are of critical importance as much as the existence. It seems that companies have an advantage in defining AI strategies in a way that makes it sound relevant but not overly redundant. The threshold effects observed in the trading volume indicate that excessive focus on AI can decrease the informational novelty especially in a setting where such accounts have become the new normal. Over the past few years, big tech companies have made a habit of emphasizing AI related endeavors, such as investing in data center capacity, dedicated hardware (e.g. GPUs), and embedding AI into their primary products and services. With such revelations becoming more standardized among the companies, differentiation is increasingly becoming based on specificity, clarity and plausible connection to execution instead of the mere frequency of mention. To the practitioners this means that in order to help people communicate effectively it is necessary to balance the degree of detail in a way that does not add too much repetition to the extent that it results in a dilution of the message.

The results associated with uncertainty give further instructions. The inverse relation between the disclosures of the structured uncertainty and the market level volatility indicates that, the disclosure of the risks associated with AI can help to stabilize the investor expectations. Among other aspects, uncertainties that are commonly experienced by the firms include regulatory innovations, infrastructure bottlenecks, model predictability, and implementation schedules. The findings reveal that the recognition of such difficulties explicitly, does not always lead to heightened perceived risk, on the contrary, it can lead to a decrease in ambiguity, by giving investors a more precise structure upon which to assess the possibilities. It can be implemented in practice by indicating that strategies of communication that involve an equal discussion of both opportunities and constraints can increase credibility and minimize misinterpretation. This becomes especially pertinent as authorities in the field of AI systems, including data governance to model responsibility, still develop in the context of jurisdiction.

The study by investors and analysts demonstrates the need to go beyond generic measures of sentiment in the assessment of corporate disclosures associated with emerging technologies. The multidimensional aspect of AI narratives can be missed by the traditional sentiment analysis that views communication as being either generally positive or negative. The findings support that thematic decomposition, which separates factors like investment, uncertainty, and performance gives more informative signals especially when using volatility as a metric. With the integration of AI into business models, analysts can find it useful to apply organized textual analysis to the evaluation models, in addition to conventional financial metrics. This would enable us to have a more subtle understanding of how companies are setting themselves in the changing technological environment.

The implications of the volatility findings with respect to the sector and portfolio management and risk assessment are also implied. The fact that AI stories have no significant correlation with overall market volatility, and moreover, effects can be found inside the technology oriented

VXN, indicate that risks related to AI are currently seen as localized to certain parts of the market. This means to investors that the uncertainty associated with AI can be better handled at the sector or thematic level as opposed to broad market hedging tactics. Nevertheless, this segmentation will not be fixed. With the expansion of AI applications into other sectors, including healthcare, finance, manufacturing, and logistics, sector related and systemic risk might become less differentiated. The observation of the development of narrative-based effects within the industry could thus be a valuable field of current analysis

On a larger scale, the results are indicative of the rising presence of qualitative information in the financial markets. Historical performance and near-term guidance have always been the main subjects of the earnings call, whereas long term strategic direction is now also being communicated during the earnings call, especially in sectors which are highly dynamic technologically. An obvious illustration of such a change is AI. The companies talk about model development, infrastructure expansion and product integration regularly, even when the financial contribution of the initiatives made to date has not become apparent. Narrative disclosures in this case present a progressive action that is a supplement, not a substitute for the conventional financial information. This develops the significance of practitioners viewing such disclosures as not peripheral commentary but rather as part of the information profile of the firm.

The research also has regulatory implications as well as governance implications. With the increased dependence of AI systems in business operations, the transparency, accountability, and risk disclosure issues would probably become more prominent. The findings indicate that structured and transparent uncertainty disclosure is likely reacted in markets, which could justify the argument that more standardized disclosure practices should be used in the context of AI related risks. Although the formal reporting rules in this field are continuously developing, the trend of the increasing role of AI in corporate strategy might contribute to the pressure of similar and regular reporting of the companies.

Regarding future research, there are several research angles that arise out of the constraints and limits of the current research. First, it would be best to extend the analysis to large technology companies to determine the generalizability of the results. Since AI is now being implemented in other industries, it would be interesting to consider whether we see the same dynamics on narrative in other industries with varying operational features. Second, extended time frames would be able to contain the dynamic between the story of AI and market performance as the technology continues to grow and permeate the business workflows as the AI wave penetrates the world further. Third, it might be possible to include other sources of data, including analyst calls, investor calls, regulatory filings, and so forth, to have a more balanced representation of how AI related information is conveyed and understood.

Also, more detailed features of the interpretation of narratives may be examined in future studies. Although the presence of the thematic content is reflected by the lexicon based approach, it fails to incorporate the contextual features like the tone in the overall themes, the credibility of the speaker, or the effect of interactions between various items of the narrative. New natural language processing methods, such as transformer models, can make it possible to analyze these dimensions more deeply. Similarly, surveys can be conducted among analysts to understand how they perceived the information from the earnings call. Lastly, experimental or quasi-experimental designs would be useful in answering questions of causality by isolating the effect of certain elements of the narrative on investor behavior under controlled conditions.

In conclusion, the results of the given research indicate that AI related corporate narratives become a growing and significant part of the informational environment in financial markets. Their effects work in different mechanisms which influence attention and risk perceptions. These effects have to be interpreted based on content and context, both. To the practitioners, it also means that to ensure efficient communication, analysis and risk management in an AI driven atmosphere, one will need to adopt a method that considers the complexity with the uniqueness of technological disclosures. In the case of researchers, it indicates the necessity of further creation of approaches and schemes that can reflect the changing role of narrative information in determining market outcomes.

5.5 Closing Remarks

This paper aimed to investigate the presence of quantifiable implications of artificial intelligence stories in corporate earnings calls in the financial market. The study went past the generalized sentiment analytic approach to take a domain dependent method to isolate AI related disclosures and assess their connection to stock price changes, volume, and volatility. All the findings help to confirm that AI narratives are not just symbolic or rhetorical artifacts, but operate as economically significant signals, which influence how investors are interpreted and the market is reacting.

Throughout the empirical investigation, a similar trend appears: AI related communication does not have a similar influence, but rather works on differentiated channels. Bullish and progressive AI news is linked to an increase in the volume of trading, which indicates that this type of disclosure, in turn, provokes the interest and involvement of investors. Meanwhile, uncertain or ambiguous AI communication is a greater source of volatility, suggesting that markets do not simply price innovation, but the explicitness and trustworthiness of AI communication as well. These findings support the notion that narrative tone, specificity, and strategic framing are the key aspects of the information processing in contemporary financial markets. Notably, the research helps to fill a gap that is of paramount importance in the literature because it combines narrative theory and quantitative financial analysis within the emerging technology context. Although thematic specificity has been observed in the literature before sentiment, this study shows the importance of the thematic specificity, which is the ability to distinguish between AI discourse and other types of discourse with specific marketing opportunities. The application of a custom dictionary based methodology also increases the transparency in the method and its reproducibility. It provides a flexible template to apply to future research in firms, industries, and historically.

When it comes to practical implications, the findings have relevant implications to corporate managers, investors, and analysts. To companies, the findings highlight the strategic value of the communication of AI initiatives not merely that they are being communicated. To the market participants, they emphasize that they need to interpret AI stories with sensitivity, knowing that various aspects of disclosure can be used as an opportunity, risk, or uncertainty indicator in unique ways.

To sum up, the paper places AI narratives at the center of the financial communication as the important and changing part. With the further development of artificial intelligence as a tool of corporate strategy, the discourse of earnings will be a critical point of contact between companies and markets. This interface is not a fringe benefit to learn anymore: to read the processes of valuation, attention and uncertainty in an ever more narrative based financial world, it is a mandatory requirement.

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APPENDIX A

Earnings Data

(Meta Platforms, Inc. (META) Earnings Call Transcripts | Seeking Alpha)

HTTPS://SEEKINGALPHA.COM/SYMBOL/META/EARNINGS/TRANSCRIPTS

(Microsoft Corporation (MSFT) Earnings Call Transcripts | Seeking Alpha,)

https://seekingalpha.com/symbol/MSFT/earnings/transcripts

(NVIDIA Corporation (NVDA) Earnings Call Transcripts | Seeking Alpha)

https://seekingalpha.com/symbol/NVDA/earnings/transcripts

(Apple Inc. (AAPL) Earnings Call Transcripts | Seeking Alpha,)

https://seekingalpha.com/symbol/AAPL/earnings/transcripts

(Alphabet Inc. (GOOG) Earnings Call Transcripts | Seeking Alpha)

https://seeklingalpha.com/symbol/GOOG/earnings/transcripts

Market Data

VXN (CBOE official): HTTPS://WWW.CBOE.COM/US/INDICES/DASHBOARD/VXN/

VIX (Federal Reserve FRED): HTTPS://FRED.STLOUISFED.ORG/SERIES/VIXCLS

Apple (AAPL): HTTPS://FINANCE.YAHOO.COM/QUOTE/AAPL/

Microsoft (MSFT): HTTPS://FINANCE.YAHOO.COM/QUOTE/MSFT/

Alphabet (GOOGL): HTTPS://FINANCE.YAHOO.COM/QUOTE/GOOGL/

Meta (META): HTTPS://FINANCE.YAHOO.COM/QUOTE/META/

NVIDIA (NVDA): HTTPS://FINANCE.YAHOO.COM/QUOTE/NVDA/

Code Libraries

R Core Team: HTTPS://WWW.R-PROJECT.ORG/

quantmod: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=QUANTMOD

ggplot2: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=GGPLOT2

readr: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=READR

syuzhet: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=SYUZHET

stringr: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=STRINGR

TTR: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=TTR

dplyr: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=DPLYR

zoo: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=ZOO

moments: HTTPS://CRAN.R-PROJECT.ORG/PACKAGE=MOMENTS

APPENDIX B

```
##############################################################
# CUSTOM AI LEXICON (FULL VERSION)
# EXACT DICTIONARY USED IN THESIS
##############################################################

custom_lexicon <- list(

  ai_optimism = c(
    "transformative","breakthrough","innovative","pioneering","revolutionary",
    "generative ai","ai mode","ai overview","ai capabilities",
    "reasoning models","foundation model","large language model",
    "ai opportunity","next generation ai","discovery engine",
    "agentic ai","advancement in ai"
  ),

  investment = c(
    "ai infrastructure","accelerated computing","training and inference",
    "ai related spend","ai infrastructure operating","compute infrastructure",
    "training cluster","hypercomputer","sovereign ai","TPU",
    "superintelligence","ai investment","capital investment",
    "scaling ai","data center ai","sovereign ai infrastructure",
```

```
  "ai factory","supercomputing","gpu cluster","gpu for ai"
),

uncertainty = c(
  "risk of hallucination","ai hallucination","uncertainty",
  "risks and uncertainties","regulatory risk","ai safety",
  "model risk","compliance","constraints","supply constraints",
  "compute constraints","regulation","volatile demand",
  "challenging environment"
),

performance = c(
  "ai powered features","ai powered tools","neural engine",
  "ai powered search","ai enterprise software",
  "generative ai applications","generative ai solutions",
  "ai adoption","strong demand for ai","ai revenue",
  "ai monetization","ai deployment","ai usage",
  "ai overviews","productivity gains","pmax"
),

ethical_ai = unique(c(
  "responsible ai","ethical ai","ai governance","export controls",
  "trust and safety","privacy preserving","data governance",
```

```
    "fairness","alignment","accountability","transparency",
    "industry standard","ai principles","safe ai","ai safety",
    "consent","responsible deployment"
  ))
)
```