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THE IMPACT OF AI ENGAGEMENT ON THE VALUATION OF GERMAN LISTED COMPANIES: AN EXPLORATIVE ANALYSIS - THE IMPACT OF ARTIFICIAL INTELLIGENCE METHODS ON FIRM'S VALUATION

PEER JUNGBLUTH

Work project carried out under the supervision of:

Professor Antonio Nogueira Leite

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List of Abbreviations

AI – Artificial Intelligence

BI – Business Intelligence

DCF – Discounted Cash Flow Method

EBIT – Earnings Before Interest and Taxes

EPS – Earnings-per-Share

FE – Fixed Effects Model

IPA – Intelligent Process Automation

NLP – Natural Language Processing

NWC – Net Working Capital

PE – Price-to-Earnings

PMS – Performance Measurement System

PV – Present Value

RE – Random Effects Model

R&D – Research and Development

ROIC – Return on Invested Capital

VIF – Variance Inflation Factor

Abstract

This explorative study investigates how AI engagement influences the valuation of German listed companies, measured through Tobin's Q. Panel data from 160 firms across the DAX, MDAX, and SDAX indices (2017–2023) is analyzed using 5 regression models. The results show a negative impact of AI Methods on Tobin's Q. These findings suggest that while AI adoption is conceptually promising, current implementations fail to deliver anticipated valuation benefits or attract sufficient investor confidence regarding future value creation.

Keywords: Artificial Intelligence, Company Valuation, Tobin's Q, Regression Analyses, German Public Market

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1 Introduction

"AI is not only for engineers. It brings changes in the dynamic of business, and we have to adapt or die." – Satya Nadella, CEO of Microsoft. As of 2024, 72% of companies worldwide are adapting to this dynamic change by implementing artificial intelligence (AI) in at least one business area (McKinsey & Company 2024). In contrast, only 37% of German companies have invested in AI, revealing a significant difference (Kasia 2024). This lag in AI adoption is particularly concerning given Germany's recent economic stagnation, as it risks causing the nation to miss out on a potential driver of future growth (Rudnicka 2024).

This concern is supported by studies that have found that AI could potentially increase economic growth rates by 1.7%. In light of this, the question arises whether closing the AI adoption gap might be an important factor in helping German companies adapt and increase their competitiveness against global competition. (Unkefer 2017)

Although significant advancements have been made in integrating AI into business operations, there is still limited understanding of how these efforts impact firm valuation (T. Kim, Park, and Kim 2022). Traditional metrics such as Tobin's Q, provide a suitable measure for investigating this relationship. Existing research often focuses on the operational improvements brought about by AI, such as increased efficiency or enhanced decision-making (Wamba-Taguimdje et al. 2020). However, the link between these operational gains and their influence on market valuation in real-world remains unclear, especially in Germany, where AI adoption is accelerating but faces unique market and regulatory conditions (OECD 2024). This thesis seeks to address this gap by analyzing how AI engagement influences the valuation of German-listed companies.

1.1 Research Question and Objectives

Therefore, the central research question guiding this work is: *How does AI engagement impact the valuation of German-listed companies?* To address this overarching question and provide a foundation for future research to build upon, this explorative study aims to achieve the following objectives: 1) Investigate the relationship between AI engagement and Tobin's Q as a measure of valuation for a more granular understanding, 2) examine how different AI methods, application areas, and development approaches contribute to firm valuation. 3) Offer insights for companies and policymakers on leveraging AI for future financial growth.

1.2 Significance of the Study

By answering those questions, this study contributes to the academic literature by extending the current theoretical understanding of AI's role beyond its direct impact on operational efficiency to its extended impact on market valuation. Our exploratory findings will serve as a foundation for scholars and practitioners to delve deeper into the subject while providing companies with insights they can adapt and apply to their own specific contexts to refine their AI engagement strategies. Furthermore, the research may inform policymakers seeking to foster AI adoption while ensuring it aligns with broader economic goals.

1.3 Structure of the Thesis

To provide a clear, academic, and empirical study that addresses the existing research gap and explores the derived research question as well as our further objectives, this thesis is structured as follows:

Chapter 2 – provides a review of relevant literature, including theoretical foundations, the definitions of AI, the mechanisms linking operational performance to valuation, and how AI interplays with said mechanisms.

Chapter 3 – describes the research methodology, including the dataset, variables, and regression models used in the analysis.

Chapter 4 – presents the results of the regression analysis, exploring the impact of AI engagement on firm valuation through multiple categories as well as the discussion of the findings in relation to our research question.

Chapter 5 – concludes the study by summarizing the findings, highlighting limitations, and offering suggestions for future research.

2 Literature Review and Theoretical Foundations

This chapter lays the theoretical groundwork for understanding the impact of a firm's engagement in AI on its valuation. It highlights the concept of valuation as a measure of a firm's worth and emphasizes the use of Tobin's Q. Furthermore, the general concept of AI is discussed to provide a basis for common understanding. Subsequently, the mechanism by which operational performance is translated into firm value is explained through a performance measurement system (PMS). Porter's Value Chain framework, combined with the EU Community Innovation Survey, will extend this system by giving a structure to the firm's AI engagement. Subsequently, AI Engagement is connected to the PMS deriving two mechanisms to theoretically assess the possible effects of AI engagement up to Tobin's Q.

2.1 Definitions and Key Aspects of Artificial Intelligence

This chapter will examine the definition of AI, its diverse classifications, applications, and development processes. Utilizing the classifications from the 2018 EU Community Innovation Survey as a reference. This methodology will enable us to systematize and identify domains where AI might have a substantial influence, illustrating its potential effects on technology and innovation. Through the examination of these factors, the study seeks to gain deeper insights into the complexity of AI.

2.1.1 Evolution of the Term

AI has changed significantly since its beginning. Introduced by John McCarthy in 1956, AI was initially described as “the science and engineering of making intelligent machines” (McCarthy 2007). This foundational definition set the stage for decades of AI research, which initially focused on systems that exhibited intelligent behavior.

As AI technology and theory advanced, definitions evolved to reflect new understandings and capabilities. For instance, Nilsson (2009) emphasized the goal of AI to make machines intelligent and capable of operating effectively within their environments. He highlighted that AI involves agents receiving percepts from their environment and performing actions, underscoring the importance of perception and action in intelligent behavior.

The adaptability of AI became a focal point in later definitions. Wang (2019) argued that intelligence involves “adaptation with insufficient knowledge and resources,” pointing to the ability of AI systems to adapt as a core feature. Recent perspectives, such as those of Kaplan and Haenlein (2019), characterize AI as a system's ability to analyze external data, acquire knowledge from it, and apply that knowledge to meet specific objectives through flexible strategies. This marks a shift from theoretical constructs to applications in real-world scenarios.

The breadth of AI's applications has also expanded. Scholars like Mondal (2020) focus on AI's capability for human-like perception and response. On the other hand, Samoili et al. (2020) offer a definition that categorizes AI based on key domains and interdisciplinary topics, reflecting its integration across various industries. These contemporary definitions reveal AI’s multifaceted nature, highlighting its role in everything from expert systems to commonsense reasoning.

The European Commission's recent proposal provides a comprehensive definition that includes AI's abilities and ethical considerations. AI systems are characterized as software (and potentially hardware) created by humans that operate in physical or digital environments by perceiving surroundings through data acquisition, interpreting the gathered data, reasoning based on this information, and determining actions to accomplish defined objectives. (European Commission 2019)

This thesis adopts the European Commission's holistic view, recognizing AI as a dynamic and evolving field that continually redefines the boundaries of machine capabilities. This perspective is instrumental in understanding AI's implications for its applications and impact on companies.

2.1.2 Breaking Down Artificial Intelligence

This chapter examines artificial intelligence through the classification framework of the EU Community Innovation Survey 2018 (CIS 2018). This survey provides an organized examination of AI methods, their application areas, and development methods. While there are various categorizations of AI discussed in literature, such as those by Russell and Norvig (2016), Fjelland (2020), Sarker et al. (2020), and Hintze (2016), this analysis follows the structure provided by the CIS. (Rammer, Fernández, and Czarnitzki 2022)

AI Methods

1) ***Machine Learning***

This category contains supervised, unsupervised, reinforcement learning, and deep learning methodologies, which are foundational to AI's ability to improve through experience without explicit programming.

Machine Learning (ML) often operates as a "black box," and therefore lacks transparency and clarity for users, complicating interpretation and trust, particularly in sensitive sectors such as finance. ("Examining the Black Box" 2020). Furthermore, ML shares ethical concerns with Image and Pattern Recognition regarding data privacy. (Stahl et al. 2023)

2) *Image and Pattern Recognition*

This category includes computer vision and visual analytics, featuring applications such as facial recognition, object detection, and medical imaging analysis, which are utilized for security, automation, and diagnostic purposes in business contexts. (Russell and Norvig 2016)

Therefore, image recognition demands substantial labeled data and computational resources, and it faces unique ethical challenges in applications such as surveillance, where privacy concerns are intensified (R. Li 2019).

3) *Language and Text Understanding*

This category includes natural language processing (NLP) and text mining technologies that help AI systems understand and process human language, with applications in translation services and chatbots. In organizations, these tools enhance customer service, facilitate communication, and make the analysis of language-based data more efficient. (Sarker et al. 2020)

However, language and text understanding AI is limited in versatility, as it is highly domain-specific and relies on extensive, often biased linguistic datasets, making it less adaptable across industries. (Rebolledo Font de la Vall and Gonzalez Araya 2023)

4) *Knowledge and Expert Systems*

Developed to imitate human competence in particular fields, these systems employ rule-based methodologies and knowledge representation strategies. They are valuable in fields that require complex decision-making based on extensive domain knowledge, such as healthcare, finance, and legal services. (Russell and Norvig 2016)

However, expert systems are not capable of adapting or learning from new data, rendering them less effective in dynamic or rapidly changing environments. (Russell and Norvig 2016)

5) *Other Methods*

"Other Methods" refers to all AI applications that are not classified within the previously mentioned primary methods. This could include more experimental methods, hybrid methods for AI, or custom applications designed for specific organizational requirements.

Application Areas

1) Products and Services

AI is a transformative force in both products and services, driving innovation and significantly changing consumer experiences. AI integration can take two forms: AI-enabled products or services, which add features like AI-driven recommendation systems or robo-advisors, and pure AI products or services, where AI is the core element providing substantial value, like autonomous vehicle software or advanced language models. In products, AI enriches functionality and interaction, while in services, it revolutionizes operations by automating and personalizing delivery, potentially redefining current service models and theories. (Neuhüttler et al. 2020)

2) Process Automation

Apart from augmenting products and services, AI has significantly boosted business efficiency through intelligent Process Automation (IPA). In contrast to traditional Robotic Process Automation, which can only perform predefined, rule-based work, IPA leverages AI and machine learning to make dynamic decisions and function independently. This integration allows IPA to handle complex and dynamic processes, substantially increasing operational efficiency and reducing human intervention (Chakraborti et al. 2020; Kholiya et al. 2021). AI's capabilities are further extended by incorporating technologies such as Optical Character Recognition, which enable the processing of large volumes of textual data, thus broadening the scope of automation applications. These advancements not only streamline workflows but also minimize the potential for errors inherent in manual processes. (Shidaganti et al. 2021; Schmitz, Stummer, and Gerke 2019)

3) Client Interaction

Artificial Intelligence is changing how customers and companies connect, reshaping the way services are delivered and how they engage with each other. Yavuz (2019) highlights the significant role of AI in customer communication, which spans from simple chatbots to more sophisticated systems that improve service capabilities and lower costs (Alzahrani 2016). Using AI in service interactions involves different applications like robotic process automation, machine learning, and deep learning (Hollebeek, Sprott, and Brady 2021). These technologies can serve in supportive roles, such as voice assistants, or take on more dominant roles in platforms like gig-work services. However, the most effective implementations often showcase a mix of human and AI collaboration, creating a partnership that enhances both efficiency and innovation (Dix 2021).

4) Data Analytics

In data analytics, AI has transformed business intelligence (BI), enabling organizations to utilize data-driven insights for strategic decision-making and operational enhancements. This evolution is characterized by the emergence of intelligent business analytics, which combines traditional BI with AI and big data capabilities, enabling organizations to leverage vast amounts of data for more informed decisions. (Eboigbe et al. 2023)

These advancements improve efficiency and accuracy in data analysis, allowing businesses to uncover hidden patterns and trends that traditional methods may overlook. (Eboigbe et al. 2023)

Moreover, the application areas of AI-driven analytics include finance, healthcare, and education, where it enhances prediction accuracy and optimizes decision-making processes. (Dix 2021). The arrival of AI has also facilitated the development of self-service BI models, enabling non-technical users to independently generate insights. The liberalization of data analytics enhances the accessibility and user-friendliness of BI tools, promoting a culture of data-driven decision-making within organizations (Eboigbe et al. 2023).

Despite these advancements, the deployment of AI in data analytics presents challenges such as data security, privacy concerns, and ethical considerations that require careful management to fully mitigate risk and utilize AI's potential (Zaripova et al. 2023).

5) Other Areas

AI's potential goes far beyond traditional categories, showcasing its versatility and impact across a wide range of fields. This category includes every application area that can't be categorized. One noteworthy application, for example, is in research and development (R&D). While not explicitly outlined in the CIS questionnaire, R&D activities involving AI likely fall within this scope.

Beyond R&D, AI's applications in "Other Areas" extend to fields like regulatory compliance, environmental sustainability, and creative industries. For example, AI can simplify regulatory processes, improve resource efficiency in sustainability efforts, and inspire innovations in art and media. Its impact on R&D has significant economic implications. Recent studies link AI's ability to enhance idea production through resource-intensive methods to potential productivity growth increases of up to twofold. (Besiroglu, Emery-Xu, and Thompson 2024).

This wide-ranging applicability underscores AI's role as a critical driver of innovation and economic advancement in today's technology-driven era.

AI Development Approaches

1) In-house Development

In-house development of AI enables companies to tailor solutions precisely to their unique needs and challenges. This strategy is based on leveraging internal resources and expertise to foster innovation that is deeply integrated into the organization's existing processes. Firms with advanced AI capabilities often achieve superior innovation outcomes due to this internal synergy. According to Rammer, Fernández, and Czarnitzki (2022), companies engaging in in-house development can exploit their specific knowledge and skills more effectively, enhancing their competitive advantages and operational efficiencies. Additionally Ileșan et al. (2023) suggest that such an approach not only facilitates customization and strategic alignment of AI applications but also significantly boosts new product development, process improvements, and cost efficiencies.

Ultimately, companies having advanced AI capabilities may achieve superior innovation results; however, for others, the large resource investment necessary could pose a significant challenge.

2) Developed by Others or Acquired

Conversely, acquiring AI technologies developed by external entities offers a route to rapidly integrate (advanced) solutions without the same internal resource commitment required for in-house development. According to Espedal (2005), while externally sourced AI solutions accelerate technology adoption and improve operational capabilities, they often lack the deep customization required to address specific organizational challenges. This trade-off frequently involves sacrificing the opportunity for tailored integration that fully addresses a company's strategic needs. (Sharma and Ho 2002; Eklof et al. 2024)

3) Mixed Development

The hybrid or mixed development approach combines in-house and externally acquired AI technologies to foster robust innovation outcomes. Rammer, Fernández, and Czarnitzki (2022) report that approximately 24% of AI-utilizing firms adopt this strategy, enabling them to balance deep, tailor-made integration with the agility to capitalize on external technological advancements. By merging internal development with external innovations, companies can optimize their AI applications, enhancing their innovation landscape while maintaining flexibility in adoption and implementation. However, this approach can raise challenges such as integration issues, data quality concerns, and increased complexity in managing in-house and externally acquired technologies. (Rammer, Fernández, and Czarnitzki 2022; Eklof et al. 2024; Nurhas, Geisler, and Pawlowski 2019)

2.2 Transition from Operational Performance to Valuation

Firm valuation refers to the analytical process of estimating the present worth of a business entity. Moreover, valuation is a fundamental practice in finance and economics, where the goal is to assign a quantifiable value to a firm. (Drukarczyk and Schüler 2021)

Value often serves as a concept for assessing a firm's financial output of its operation. Furthermore, it functions as a "north star" metric due to its significant relevance for organizations (Koller, Goedhart, and Wessels 2010). The underlying central role aligns with Lonkani (2018) who argues that firms primarily exist to generate value, even though the nature of value remains subject to discussion. In literature, the inherent assumption is that value is understood as economic value (Agle, Mitchell, and Sonnenfeld 1999). However, there is ongoing debate regarding how to operationalize value. Hungenberg and Wulf (2021) identified two prominent schools of thought on this matter: the shareholder value theory and the stakeholder value theory.

2.2.1 Operationalization of Value

1) Stakeholder Value Theory

The stakeholder theory, largely developed by R. Edward Freeman, is a management philosophy that suggests companies should align their actions with the interests of all groups essential to the organization's success (Freeman, Wicks, and Parmar 2004)

In essence, the core goal of the stakeholder approach is to balance and satisfy the interests of all groups involved. Therefore, it can be assumed that within the stakeholder theory framework, value signifies the aggregate value of all stakeholders (Hungenberg and Wulf 2021). Even though financial performance may be important to many of a company's stakeholders, it is not the only aspect of value that matters to them. Instead, Harrison and Wicks (2013) suggest adding other non-financial benefits stakeholders seek when engaging with an organization to the pure economic benefits.

However, a limitation of the stakeholder approach lies in the operationalization of value. This becomes clear when considering how stakeholder value can be determined. It consists of the costs and benefits each stakeholder group gains from their connection with the company. While maximizing value for one group may be straightforward, companies must aim to increase value for every group. Yet, optimizing overall stakeholder value does not simply equate to summing the individual values for each group. Furthermore, the benefits to stakeholder groups would need to be balanced against each other. However, this is hardly achievable in practice. (Oubihi and Elouidani 2016; Hungenberg and Wulf 2021)

2) Shareholder Value Theory

Unlike stakeholder theory, Milton's shareholder theory, introduced in 1970, argues that a firm's primary responsibility is to serve its shareholders alone. According to Friedman (1970), the primary goal and duty of a business is to maximize shareholder value. Thus, it operationalizes in generating profits and creating financial returns for its owners. (Williamson and Babcock 2020)

However, critics suggest that a strict focus on shareholder value can lead to negative long-term consequences. One reason is that this approach often encourages a short-term focus on quickly increasing company value. Another reason is that it may ignore the interests of other stakeholders, like employees, customers, and communities, leading to one-sided decisions. Conversely, scholars contend that adopting a long-term perspective on shareholder value, as opposed to a short-term one, may resolve this issue. They argue that the cumulative impact of a firm's operations on stakeholders will ultimately be reflected in financial metrics that, in turn, calculate the corporate value or shareholder value. (Largani, Kaviani, and Abdollahpour 2012)

Both shareholder and stakeholder theories offer frameworks for defining value based on different group interests. Kucukyalcin (2018) argues that theories can complement each other; long-term shareholder value often relies on satisfying all key stakeholders. Thus, shareholder value can be viewed as a long-term, multi-dimensional framework (Hungenberg and Wulf 2021). For this reason, in this work, value is defined using the shareholder value approach.

2.2.2 Valuation Metrics

In both academic and practical contexts, various metrics are employed to operationalize the shareholder value of companies.

1) Present Value

Value is often measured by a company's market value, calculated as the present value of all expected future cash flows (Basci 2019).

According to Gaspars-Wieloch (2019) the present value (PV) of a firm is determined using an equation where PV represents the firm's current valuation, CF_t denotes all expected future cash flows, r signifies the required return rate for investors, and g is the expected growth rate of future cash flows. In cases involving perpetuities, the formula simplifies to account for the infinite nature of cash flows. As described by S. Johnson (2020), the present value of a level perpetuity with constant growth is calculated as:

$$PV_0 = \frac{CF_t}{r - g}$$

However, PV might not always reflect true market valuations, as these are often based on speculative and potentially inaccurate assumptions concerning growth and discount rates. These uncertainties could lead to discrepancies between company's PV actual market value (Penman 2011). Thus, it can be derived that present value may not fully represents a comprehensive measure for assessing shareholder value.

2) Tobin's Q

On the other side, Tobin's Q is employed as a key metric to evaluate a firm's value taking a market angle into account. It indicates whether a company is overvalued or undervalued relative to its physical asset replacement costs. Developed by Brainard and Tobin (1968), Tobin's Q is defined as the following ratio:

$$Tobin's\ Q = \frac{Market\ value\ of\ a\ firm}{Replacement\ costs\ of\ its\ assets}$$

Consistent with Fu, Parkash, and Singhal (2024), the market value of a company is estimated as the market value of equity, hence market capitalization, plus the market value of debt, assuming that the market value of debt equals the book value. Bendle and Butt (2018) have recognized that the replacement cost of a firm's assets remains often indeterminate, which leads scholars to frequently employ approximations that rely on a variant of the book value. Similarly, Erickson and Rothberg (2009) advocate for utilizing the book value of assets as a reasonable proxy. We adhere to this suggestion, whereby the following approximate formula for Tobin's Q is utilized:

$$Approximated\ Tobin's\ Q = \frac{Market\ Capitalization + Debt}{Total\ Assets}$$

A Tobin's Q value of more than one indicates that a company may be overvalued and that there is, therefore, potential value creation for shareholders and vice versa (Lewellen and Badrinath 1997). Furthermore, Fu, Parkash, and Singhal (2016) present empirical evidence demonstrating a positive correlation between Tobin's Q and firms' future operating performance.

2.2.3 Interconnection of Operational Performance and Tobin's Q

To comprehend the influence of AI on Tobin's Q, it is essential to first identify its application within a firm and understand how these applications affect Tobin's Q. AI is predominantly employed to enhance a firm's operations (Wamba-Taguimdje et al. 2020; Grover, Kar, and

Dwivedi 2022). This enhancement serves as the initial focal point for the analysis. Assuming a baseline scenario where a firm maintains steady operations and external influences, it would achieve a certain valuation. Integrating AI at the operational level may enhance, diminish, or sustain the firm's valuation. This study employs a PMS to rationalize this causal relationship.

PMS are widely utilized in academia and practice as tools to link operational metrics and establish relationships between them. As they assist in explaining complex relationships, such a system is employed in this work to describe the correlation between a firm's operations and Tobin's Q (Sandt 2013). These theoretical mechanisms and causal chains serve as a framework to which artificial intelligence is added to determine whether and how it might alter this valuation.

To construct the PMS, mechanisms previously explored in academia are interconnected. Thus, a top-down approach is employed, examining Tobin's Q formula and its components.

1) Nominator

Figure 1[1] outlines the factors that determine market capitalization, organized through a PMS:

[1] The relationships depicted within the PMS are considerably more complex in reality than presented herein. For the purposes of this thesis, the primary casual chains have been intentionally isolated.

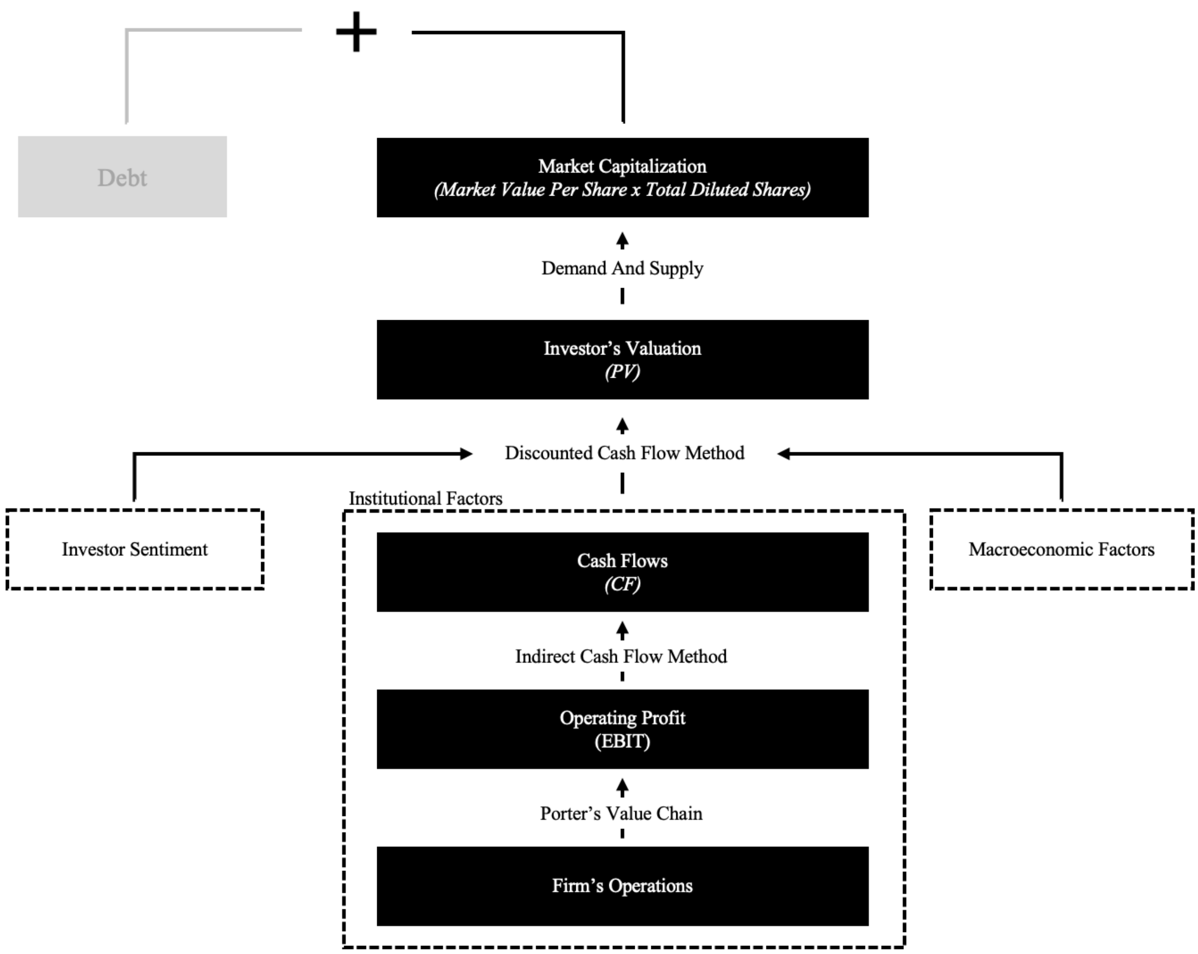

Figure 1: Performance Management System – Nominator (own illustration)

Delving deeper into the numerator of Tobin's Q, other scholars have identified that it primarily consists of debt along with market capitalization as seen in chapter 2.2.2. Due to the exploratory nature of this study, the focus lies on isolating the impact of a firm's operations and its performance on Tobin's Q. Consequently, debt considerations are deliberately excluded from the analysis to allow for an unbiased examination. Market capitalization has been analyzed through various methodologies based on stock market data (Bonga and Sithole 2019). According to Moro-Visconti (2022), market capitalization can be calculated using the following formula:

$$Market\ Capitalization = Market\ Value\ per\ Share\ x\ Total\ Diluted\ Shares$$

Prior studies have further investigated the influencing factors on market capitalization, distinguishing its driver into three primary categories: institutional factors, macroeconomic factors, and investor sentiment. These factors are integrated when investors evaluate the firms value through approaches like discounted cash flow method (DCF). (Phuong 2020)

In this context, Garcia and Liu (1999) argue that macroeconomic factors contribute to explaining variations in market capitalization. However, they are beyond the control of individual firms and are thus often excluded from firm-level analyses.

According to López-Cabarcos et al. (2020) investor sentiment can be defined as the optimism or pessimism of investors regarding future stock value development. It encompasses the way investors form their beliefs about the future performance of a firm and it's share value. They further argue that high levels of investor sentiment can lead investors to be overly optimistic about the future earning power of a firm, which can drive up the valuation premium they add upon the fundamental value.

On the other hand, Pavone (2019) posited that a firm's financial performance metrics represent significant determinants of market capitalization. Brainard, Shapiro, and Shoven (1990) add that the market value of a firm is intrinsically linked to its ability to generate future earnings. This perspective is supported in financial literature, with Fu, Singhal, and Parkash (2016) asserting that a firm's market value is determined by the discounted value of its expected future cash flows generated by its assets.

Assessing, structuring, and transforming expected future cash flow in a firm's value is a well-studied endeavor in financial analysis and can be accomplished through a variety of methodologies. Among the most prominent is the DCF (Fernández 2001). The DCF methodology systematically structures the firm's projected cash flows, investor sentiment and macroeconomic factors, and transforms these into an estimated present value. This can then be interpreted as the firm's earning power. Central to the DCF approach is the concept of free cash flows (FCF), which represents the cash generated by the firm that is available to investors after accounting for necessary operational and capital expenditures (Jennergren 2011).

The calculation of FCFs begins with Earnings Before Interest and Taxes (EBIT), a measure of operating profit. To this figure, depreciation is appended; subsequently, taxes, capital expenditures, and any augmentation in Net Working Capital (NWC) are deducted. EBIT is particularly significant as it isolates the performance of the firm's core operations, excluding non-operational income, taxes, and financing effects. (Yaari et al. 2016)

Literature provides alternative ways to contextualize the operational processes that drive this operating profit. A prominent approach is Michael Porter's value chain analysis, which offers a structured framework for understanding how firms achieve competitive advantages that ultimately result in operating profits. By systematically allocating direct and indirect costs as well as revenues to respective segments of the value chain, one can determine an operating profit at each stage. Assuming comprehensive coverage of all business activities within these allocations, the sum of the profits from all segments provides an aggregate EBIT figure. This allocation allows for granular analysis of the profit generation and, simultaneously, provides a way for structuring the AI engagement on an operational level. In this context, according to Porter (1985) firm's activities can be divided into primary and support categories: 1) The primary activities – inbound logistics, operations, outbound logistics, marketing and sales, and service – directly create and deliver products or services to customers. 2) The support activities – firm infrastructure, human resource management, technology development, and procurement – provide essential resources and systems that enhance and support the primary activities.

2) Denominator

According to Nieto and Pérez (2002), total assets are fundamental in defining a company's position within the market and the economy, as they encapsulate the entirety of resources utilized for profit generation. This stands in contrast to the outcome-focused view presented in the previous chapter, which emphasizes outcomes. Instead, this section adopts a resource-oriented perspective while underscoring assets as the foundational elements for profit generation.

Total assets at book value represent the sum of all company assets valued according to accounting standards. This allows for easier operationalization compared to the nominator of Tobin's Q, as the relevant figures can be derived from financial statements. The total includes current assets like cash, accounts receivable, and inventory, valued at the lower of cost or market price to provide a conservative estimate of the company's short-term financial position. The formula also covers long-term investments such as stocks, bonds, and real estate. Additionally, property, plant, and equipment (PP&E) – tangible assets essential for operations – are recorded at the purchase price and depreciated over their useful lives to account for wear and tear. Intangible assets like patents and trademarks are amortized over their useful lives, except for goodwill, which is assessed annually for impairment. Other assets, including long-term prepayments and deferred tax assets, are valued based on the future economic benefits they provide. (Pilz 2019)

To maintain consistency with the previous chapter, these assets can be further categorized not only by their accounting classifications but also by the activities in which they are employed, aligning with Porter's Value Chain analysis. This categorization serves as a basis for examining where AI is applied, subsequently analyzing how the deployment of AI influences the composition and value of total assets.

2.3 Mechanisms of AI Engagement

The following chapter explores how AI can be integrated into the previously established causal chain. As defined, AI is deployed at the operational level and is thus anchored within a firm's operations. To provide a clear structure, the chapter uses Porter's Value Chain framework to cluster the AI engagement and analyze its effects on operations. Based on these insights, two general mechanisms of AI Engagement impacting Tobin's Q are distilled.

2.3.1 Impact of AI on an Organization's Performance

In this context, this thesis utilizes Porter's value chain model to analyze and provide a structure on how artificial intelligence can improve a firm's performance. As scholars have established, the success in terms of shareholder value creation of a firm's operations is defined by objectives such as quality, speed, dependability, flexibility, and cost (Slack, Chambers, and Johnston 2010).

Recent findings underscore AI's growing role in boosting operations and productivity. For instance, Wamba-Taguimdje et al. (2020) report that 91% of organizations anticipate productivity gains through generative AI, while companies have achieved notable financial improvements by leveraging AI for operational optimization. These examples highlight AI's potential to drive competitive advantage and operating profits when integrated effectively into the value chain.

Yet, one should consider the substantial initial costs involved in AI adoption, including those for infrastructure and training employees. (Bughin et al. 2018)

The following examination will connect AI's impact on operational performance, with resulting implications for firm valuation, specifically Tobin's Q.

I. Primary Activities

1) Inbound Logistics

The integration of AI in inbound logistics improves operational efficiency and financial performance, influencing Tobin's Q. AI-driven methods, such as machine learning and deep learning, enhance the precision of demand forecasting, thereby minimizing stock-outs and excess stock while increasing inventory turnover rates. The higher turnover reduces holding costs and improves EBIT, a crucial element in discounted cash flow (DCF) models utilized to assess market value as seen in Figure 1. (Fernández 2001)

In supplier management, artificial intelligence tools like Bayesian networks and support vector machines provide enhanced insights into supplier performance, reducing risks and decreasing lead time variability, thereby boosting profitability (Fu, Parkash, and Singhal 2016; Baryannis et al. 2018). Moreover, AI enhances restock and transportation processes, reducing costs and expediting delivery times (Boute and Udenio 2021). Although initial implementation expenses are significant, the long-term advantages—such as decreased cost of goods sold (COGS), increased EBIT, and stabilized cash flow—are considerable. (Adesoga et al. 2024)

2) *Operations*

Artificial Intelligence impacts operations by improving equipment effectiveness, production efficiency, and flexibility. In manufacturing, AI-driven predictive maintenance reduces unexpected downtime, allowing more efficient production cycles, lowering maintenance expenses, and enhancing operational profitability (Lee, Azamfar, and Singh 2019). Furthermore, AI enhances production lifecycle management and responsiveness to market fluctuations, allowing companies to adjust to evolving demands. (Bruno 2024) emphasizes that this agility reduces inefficiencies, improves operational stability, and maintains profitability.

In agriculture, AI enhances resource allocation, decreasing variable costs and improving cost-efficiency metrics. (Ganeshkumar et al. 2023) illustrate how these efficiencies reduce operational costs and enhance operating profit via improved resource utilization.

3) *Outbound Logistics*

AI-driven routing systems optimize delivery schedules, particularly for perishable goods, reducing transportation costs and improving on-time delivery rates. These advancements can decrease operational expenses. (Baryannis et al. 2018)

Fleet management also benefits from AI, which minimizes empty miles and maximizes asset utilization. Grazia Speranza (2018) shows that AI-powered systems reduce fuel consumption and operating costs. Improved operational reliability further strengthens investor confidence.

AI’s contributions to sustainability in outbound logistics, such as reduced fuel consumption while reducing costs, also indirectly enhance market valuation by supporting a positive corporate reputation and strengthening stakeholder perceptions. (Peloza et al. 2012)

Integrating AI into outbound logistics reshapes financial outcomes by improving delivery accuracy, cutting transportation costs, and maximizing asset utilization. These advancements lead to higher revenues through enhanced customer satisfaction and lower COGS and operating expenses by increasing efficiency and reducing fuel consumption. The resulting improvements in gross profit margins, EBIT, and cash flow stability are further complemented by AI’s contributions to sustainability, strengthening corporate reputation and investor confidence.

4) Marketing and Sales

AI in marketing and sales can optimize customer retention, sales efficiency, and customer engagement.

Neural networks, for example, improve predictive accuracy for customer behavior, as shown by Chen and Lin (2019). This enhanced understanding enables firms to develop more effective marketing strategies, reducing customer acquisition costs and increasing conversion rates.

AI-driven tools for segmentation and churn prediction further optimize customer retention and sales efficiency. Martínez-López and Casillas (2013) highlight that these advancements ensure sustainable future cash flows, directly enhancing FCF and market valuation (Fernández 2007).

Additionally, AI enables hyper-personalized marketing, dynamic pricing, and automated customer service using advanced technologies like natural language processing (Vijayakumar 2023).

These improvements lower operating costs, boost conversion rates, and sustain cash flows, increasing EBIT; therefore, they boost market valuation and Tobin's Q by improving financial performance and investor confidence.

5) Service

Service is impacted by AI through customer satisfaction, operational reliability, and workforce productivity.

Huang and Rust (2018) show how AI enables predictive and personalized service delivery, improving customer satisfaction and retention.

AI also reduces service downtime through predictive failure detection, lowering costs and improving (Bock, Wolter, and Ferrell 2020). Additionally, AI-powered tools for performance prediction and skill gap analysis enhance workforce productivity, reducing inefficiencies.

As shown, the utilization of AI significantly enhances service operations by boosting customer satisfaction and retention, minimizing service downtime, and optimizing workforce productivity. These improvements not only reduce costs but also increase EBIT.

II. Support Activities

1) Firm Infrastructure:

Kitsios and Kamariotou (2021) emphasize that AI supports key elements of firm infrastructure, such as management structures, information systems, financial management, legal frameworks, and risk management, enhancing overall efficiency, accuracy, and agility. By integrating AI-powered analytics and advanced machine learning algorithms, firms gain real-time insights for strategic decision-making, optimizing resource allocation and improving operational efficiency (Jarrahi 2018; Duan, Edwards, and Dwivedi 2019).

These advancements can lower costs related to delays or suboptimal decisions, optimize operational spending, and improve risk evaluation and forecasting precision. This effect boosts revenue growth by enhancing decision-making and agility, decreases COGS through optimized resource utilization, and minimizes operating expenses via improved risk management. As a result, these efficiencies enhance gross profit, and elevate EBIT.

2) *Human Resource Management*

Utilizing AI in HRM directly elevates firm performance by refining recruitment efficiency and fostering better employees.

Strohmeier and Piazza (2015) highlight how AI-driven applicant tracking systems (ATS) improve the precision and speed of candidate screening, reducing time and costs associated with traditional hiring methods. Lower hiring costs contribute to reduced operational expenses, while improved quality of hires enhances workforce productivity, ultimately increasing Earnings Before Interest and Taxes.

Beyond recruitment, AI also supports employee development by identifying performance gaps and providing actionable insights for tailored training programs. Tambe, Cappelli, and Yakubovich (2019) found that AI-powered systems significantly enhance workforce engagement and productivity by predicting performance and skill needs. These improvements can reduce turnover rates and lower associated rehiring and training costs.

Overall, AI in HRM can lead to improved gross profit and EBIT, with stable operations and cost savings.

3) *Technology Development*

AI in technology development can accelerate R&D processes and enhance innovation, with the potential to significantly influence operational and financial metrics.

For example, Chen et al. (2018) highlight that AI applications in drug discovery improve the speed and accuracy of predicting molecular behaviors, reducing time-to-market for new products. Faster R&D cycles and lower R&D costs improve innovation.

Cockburn, Henderson, and Stern (2018) further emphasize the economic impact of AI, showing that firms with AI-driven R&D processes have a 40% higher success rate in patent applications. This improvement in intellectual property generation strengthens the firm’s competitive position and innovation output. Enhanced innovation capability creates valuable products and services.

In summary, AI in technology development can boost revenue through faster product innovation, reduces COGS by lowering R&D and resource costs, and cuts operating expenses via streamlined processes. This results in a higher gross profit, which influences EBIT.

4) Procurement

Artificial intelligence influences procurement by enhancing sourcing, contract management, and complex negotiations.

According to (Handfield, Jeong, and Choi 2019), AI-driven spend analysis tools reliably identify cost-saving opportunities and therefore can enhance supplier selection. These efficiencies can reduce procurement expenses, enhancing cost effectiveness.

Artificial intelligence can also enhance strategic negotiation. (Schulze-Horn et al. 2020) discovered that AI tools enhance negotiation strategies by utilizing extensive datasets to minimize bounded rationality. This can enhance supplier competition, reduces costs, and improve supplier relationships.

According to (Slack, Chambers, and Johnston 2010), artificial intelligence facilitates procurement objectives such as cost reduction, quality enhancement, speed, and reliability. AI augments operational efficiency by incorporating these enhancements throughout the value chain, optimizing procurement-related interactions.

Overall artificial intelligence in procurement can enhance gross profit and EBIT.

2.3.2 Derived AI Impact Mechanisms on Tobin's Q

The previous chapter examined the influence of artificial intelligence on operational performance by structuring the engagement through Porter's Value Chain. In general, there can be two mechanisms derived, on how AI can impact Tobin’s Q: 1) investor valuation adjustments and 2) investments and costs as seen in the following illustration:

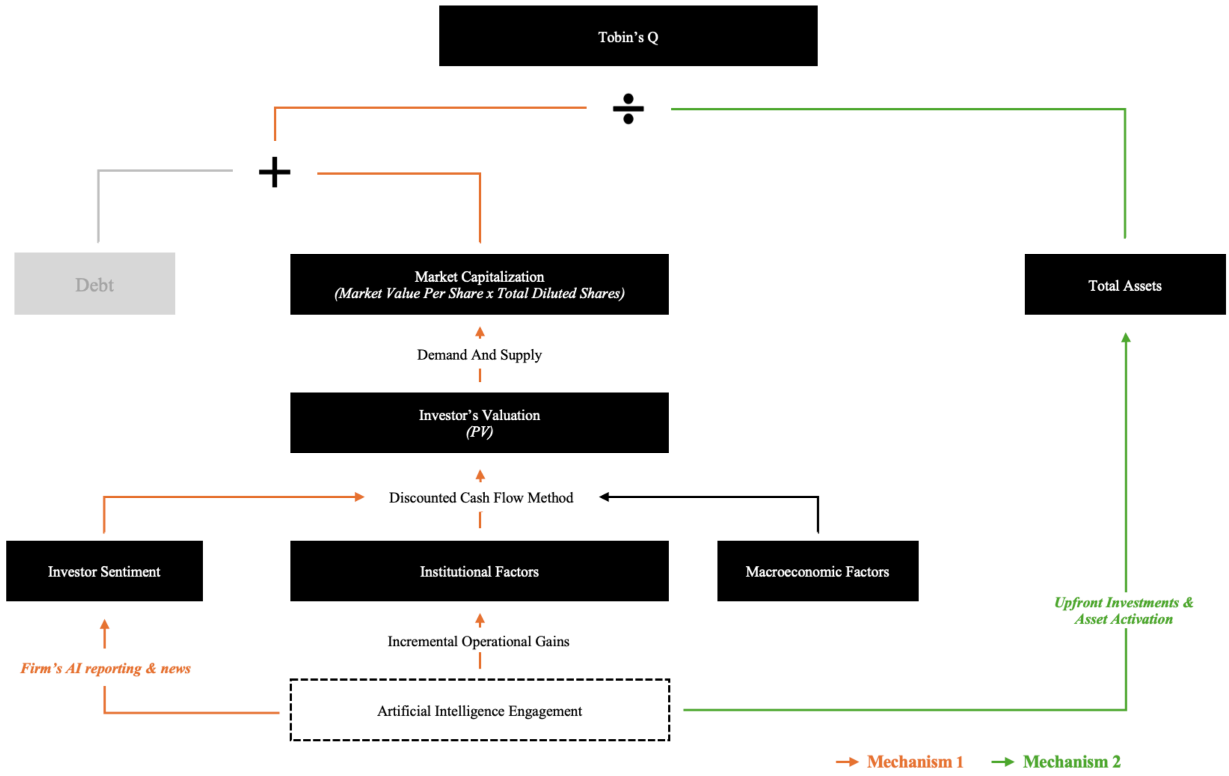

Figure 2: AI Impact Mechanisms (own illustration)

Mechanism 1

The integration of AI technologies can influence how investors approach valuation and consequently market capitalization. This influence primarily arises from two sources: changes in operational performance and shifts in investor sentiment regarding the firm’s future earnings potential.

The impact on operational performance becomes evident in key financial metrics that underpin the Discounted Cash Flow model – EBIT and cash flows. As demonstrated in chapter 2.3.1, implementing AI solutions can for example alter a firm’s efficiency and revenue generation. These changes often translate into either higher or lower EBIT and cash flows.

Second, as seen in chapter 2.2.3, investor sentiment also plays a pivotal role in shaping valuations. When firms communicate their AI strategies through public disclosures, they provide signals that inform investors' expectations. Investors anticipate a certain outcome from AI integration, which might differ from the actual outcome in the future. This outlook can, therefore, lead to adjustments in the assumptions for the DCF model, mainly being the discount and growth rate. Over time this effect will become less prominent, as the actual impact on the earning power will become evident.

Mechanism 2

In some cases, investments in artificial intelligence lead to increases in a firm's total assets. Under certain accounting guidelines, such as German accounting standards (HGB) or International Financial Reporting Standards (IFRS), expenditures associated with developing AI-related software or acquiring licenses could be recognized as intangible assets, assuming they are anticipated to provide future economic benefits. In this way, some costs may be recorded as assets rather than immediate expenses. This implies that in case those costs are not activated in the balance sheet, they will still affect Tobin's Q through mechanism 1, as they increase EBIT. Additionally, investments in specialized hardware – such as GPUs, servers, and related infrastructure – can also be classified as assets, provided that they fulfill the relevant criteria set forth in HGB or IFRS. The increase of the total assets, ceteris paribus, would then translate into a lower Tobin's Q through the increase of its denominator. (Deubert and Lewe 2021; PwC 2024).

2.4 Factors Influencing AI's Engagement

While AI has demonstrated significant potential to enhance operational performance and, therefore, Tobin´s Q across various aspects of the value chain, its impact is not uniform across all organizations. Research indicates that several key factors influence the effectiveness and extent of AI's impact on operational efficiency. Two critical factors that have emerged from the literature are company size and industry characteristics. (Na et al. 2023a; Yang, Blount, and Amrollahi 2024)

2.4.1 Company Size

The influence of company size on AI adoption and its impact significantly affects operational performance across organizational scales. Research shows that larger firms have substantial advantages in AI implementation due to their financial and infrastructural resources, including AI talent (Bughin et al. 2018; Yang, Blount, and Amrollahi 2024). These resources enable investment in advanced AI technologies and their integration across functions such as client management and predictive analytics (Brynjolfsson and McAfee 2017; Yang, Blount, and Amrollahi 2024).

However, the relationship between company size and AI impact is not strictly linear. Alekseeva et al. (2021) identified a non-linear relationship, with medium-sized firms showing the highest propensity for AI adoption due to an optimal balance between resource availability and organizational flexibility. Large enterprises often face challenges integrating AI due to internal resistance to change, impeding adoption speed and scope. (Ransbotham et al. 2017; Hupfer, Ammanath, and Jarvi 2020).

Moreover, larger firms must navigate complex regulations and manage cross-functional collaborations, which can slow AI implementation processes (Yang, Blount, and Amrollahi 2024). In contrast, smaller firms and SMEs, despite limited resources, often demonstrate greater agility, enabling rapid AI implementation in targeted, high-impact applications like customer service optimization and task automation (Yang, Blount, and Amrollahi 2024; Lee, Azamfar, and Singh 2019). SMEs leverage AI to exploit niche markets and drive innovation, despite struggling with limited AI-ready infrastructure and specialized talent .

The impact of AI on innovation also varies with company size. Grashof and Kopka (2023) note that large firms are better positioned to capitalize on AI for innovations, leveraging established R&D and cross-departmental capabilities. Conversely, SMEs focus on more adaptive and entrepreneurial AI applications within narrower scopes. Key factors influencing AI's impact include financial resources, data availability, infrastructure, organizational flexibility, and AI talent access.

Na et al. (2023) found that larger firms are more likely to invest in extensive employee training, enhancing AI's ease of use and usefulness. Additionally, Kinkel, Baumgartner, and Cherubini (2022) emphasize the importance of R&D intensity in AI adoption, typically higher in larger firms due to greater financial resources.

In conclusion, while larger companies have resource and data advantages, smaller companies can leverage their agility for transformative AI implementations. The effectiveness of AI adoption and its operational impact depend on aligning AI strategies with specific organizational contexts and overcoming implementation challenges. Understanding these differences is crucial for policymakers and business leaders to support effective AI adoption across different company's sizes.

2.4.2 Industry Characteristics

The impact of artificial intelligence on operational and, therefore, financial performance varies across industries due to sector-specific factors. This variation is driven by regulatory landscapes, data availability, and technological readiness.

One primary driver is the regulatory environment. Heavily regulated industries like healthcare and finance face unique AI adoption challenges and opportunities. For instance, Davenport and Kalakota (2019) found that AI can significantly improve diagnostic accuracy in medical imaging, though stringent data privacy regulations like HIPAA[2] in the USA often slow adoption. Conversely, the financial services industry has rapidly adopted AI, with 90% of UK firms using AI, facilitated by established regulatory frameworks for algorithmic trading and risk management (Quest, Oest, and Townson, n.d.)

Data availability and quality crucially impact AI's effectiveness. Sectors with access to large, structured datasets see significant AI benefits. Jiang et al. (2017) highlight AI's transformative role in healthcare, enabling real-time risk assessment and decision support. Jan et al. (2023) note that AI in finance aligns with the ability to process extensive, high-quality datasets, enhancing complex risk modeling and decision-making.

In manufacturing, deep learning models like DenseNet121 and DeepLabV3 enhance defect detection reliability, substantially improving operational performance (Adeyemi 2024). Service-oriented sectors like hospitality utilize AI-driven chatbots to manage about 80% of routine inquiries, showcasing AI's versatility in addressing sector-specific operational challenges (Adeyemi 2024).

Industry digitization also influences AI benefits. Chui et al. (2023) found that telecom companies using AI for network optimization saw a 10% reduction in capital expenditures and a 20% decrease in operational expenses. However, Dinmohammadi (2023) notes that smaller manufacturing firms often struggle with scaling AI systems due to insufficient data quality and digital readiness.

Competitive industries like retail and media invest heavily in AI for an edge. Gomez-Uribe and Hunt (2016) estimate that Netflix's recommendation system saves the company $1 billion annually through enhanced user engagement and reduced subscription cancellations.

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[2] Health Insurance Portability and Accountability Act

In conclusion, the effectiveness of AI in enhancing operational efficiency is significantly modulated by industry-specific characteristics. Regulatory environments, data availability, core business processes, digital maturity, and competitive pressures all play crucial roles in determining how effectively AI can be leveraged across different sectors. As Anantrasirichai (2021) suggests, industries with lower digital maturity or less standardized data face barriers to AI adoption, necessitating targeted investments in infrastructure and skills to fully realize AI's transformative potential.

2.5 Research Gap and Contribution

As demonstrated, there is a theoretically founded link between an organization's operational performance and its valuation (relationship 1). Furthermore, the impact of artificial intelligence on a company's valuation as discussed in the previous chapters, was theoretical explored (relationship 2). However, there is no extensive research conducted in a German context, that has yet examined whether relationship 2 is applicable in a real-world context.

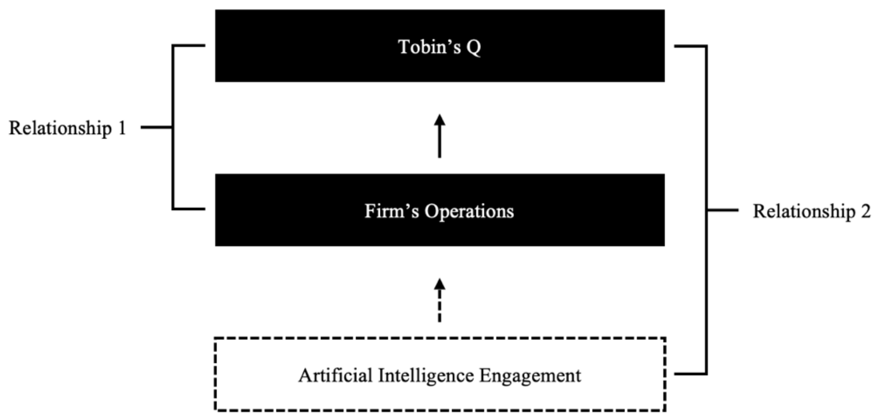

Figure 3: Interconnection of AI Engagement and Tobin's Q – simplified (own illustration)

This explorative study addresses this gap by investigating the relationship between AI engagement and market valuation using Tobin's Q. In doing so, it aims to broaden the understanding of the role of AI beyond operational improvements and provide new insights into its potential impact on the over- or undervaluation of firms. This approach contributes to the academic discourse and provides a starting point to build tailored practical guidance for companies seeking to align their AI engagement strategies with market expectations.

2.6 Hypotheses Development

In this chapter, we carefully formulate hypotheses drawn from the theoretical insights explored in previous discussions. These hypotheses are rooted in the evidence that AI integration significantly boosts operational efficiency, enhances strategic decision-making, and improves financial performance. This exploration into the transformative potential of artificial intelligence within business operations is critical for understanding its impact on firm valuation, particularly when assessed through the crucial metric of Tobin's Q.

Hypothesis 1: AI Engagement Positively Impacts Tobin's Q

This thesis hypothesizes that AI engagement within a company's operations and strategy enhances overall firm valuation. The literature supports that such integration streamlines processes, optimizes costs, and elevates productivity, which are essential for improving market valuation indicators like Tobin's Q (Wamba-Taguimdje et al. 2020). This hypothesis stems from the belief that AI engagement is crucial for driving up a firm's market worth.

Hypothesis 2: Every Type of AI Method Positively Impacts Tobin's Q

Companies can engage with the help of different AI methods, which was outlined earlier. We also mentioned that each method has its impact on the company's operations and performance. Therefore, it is proposed that each method contributes positively to operational efficiencies, thereby positively impacting the firm's valuation.

Hypothesis 3: Every AI Application Area Positively Impacts Tobin's Q

Artificial Intelligence deployment across a wide range of business domains, including product and services, process automation, client interaction, and data analytics, offers distinct advantages that collectively boost firm valuation. This thesis hypothesizes that enhancements driven by AI in these areas improve key operational metrics, such as EBIT and cash flows, which positively impact the firm's market valuation.

Hypothesis 4: Every Type of AI Development Positively Impacts Tobin's Q

The development approach to AI, whether in-house, external, or hybrid, can significantly influence its effectiveness and strategic alignment. We argue that each development strategy carries unique advantages that bolster competitive positioning and operational efficiency, thus positively affecting Tobin's Q.

By investigating these hypotheses, we aim to provide a granular understanding of how various dimensions of AI, general engagement, methods, application areas, and development strategies affect firm valuation, as indicated by Tobin's Q. This exploration is designed to help answer the research question and enrich the academic discourse on AI's impact and equip business leaders with actionable insights for leveraging AI technologies effectively.

3 Research Methodology

In Chapter 2.2.3, we utilized Porter's value chain to systematically structure AI applications. This approach facilitated an exploration of the theoretical interactions between AI applications and Tobin's Q. Moreover, it was demonstrated that the impact of AI on EBIT, and consequently on Tobin's Q, varies depending on where AI is implemented.

This, combined with the identified research gaps, prompted us to refine this approach further and adopt a more detailed methodology to understand how the deployment of AI in various forms, types, and areas of engagement differs, thus aiming for deeper insights. Therefore, we lay the methodological groundwork for our empirical analysis of how artificial intelligence impacts the valuations of German-listed companies. This chapter serves as a bridge from the theoretical discussions in previous sections to the hands-on analysis that will follow.

The following chapters detail the construction of the dataset used for the regression analysis, describing the framework, variables involved, and data collection methods. Furthermore, the structure and methodology of the regression analysis are discussed, including the choice between fixed and random effects models, the utilization of the Hausman test to determine model suitability, and the examination of various factors that affect the model's outcomes. These elements form the basis of our analytical approach.

3.1 Dataset

For the transition from theoretical discussion to practical application, we constructed a dataset that formed the basis of our empirical analysis. This chapter outlines the systematic framework we have developed for organizing, defining, and capturing AI-related variables in our dataset. We detail the criteria for selecting the variables essential to testing our hypotheses and describe the data collection methodology. By establishing a robust data foundation, we ensured the reliability and relevance of our empirical analysis aimed at uncovering the impact of AI on the valuations of German-listed companies.

3.1.1 Dataset Framework

The dataset was constructed in two parts. The first part includes the collection of all necessary financial control variables. The second part consists of four categories for which we gathered data for each company based on each category.

For this purpose, the AI categories identified in the EU Community Innovation Survey (Rammer, Fernández, and Czarnitzki 2022) were adopted to create a framework. This allows for a detailed examination and provides more practical insights into how AI impacts company valuations in the context of the theoretical foundation previously described. By exploring these categories, we aim to provide a more detailed understanding of AI's role across different business contexts.

Table 1 shows how we organized the data into four categories: general AI engagement, accompanied by the three categories from the EU Community Innovation Survey. Each variable in the respective category is measured as a count displaying how many times the company engaged in the respective category.

General AI	AI Methods	AI Application Areas	AI Development Approachs
- AI Engagement	- Machine Learning	- Products and Services	- In-house Development
	- Image and Pattern Recognition	- Process Automation	- Developed by Others or Acquired
	- Language and Text Understanding	- Client Interaction	- Mixed Development
	- Knowledge and Expert Systems	- Data Analytics	
	- Other Methods	- Other Areas	

Table **1**: AI Categories adopted after Rammer et al. (2022)

3.1.2 Variables

After establishing the framework for our dataset, we further defined the variables necessary to collect data for conducting our regression analysis to evaluate our hypotheses. We organized these variables into two categories:

1) ***Financial Control Variables***

We collected data on various financial metrics to derive the best set of control variables for explaining Tobin's Q in the context of AI engagement within our model. The control variables included in our dataset are:

Financial Variables		
ROIC	EPS	Total Liabilities
Tobin's Q	GICS Industry	Debt-to-Equity
PE	GICS Sector	EPS 1-Year Growth
Market Cap	R&D Intensity	EBITDA to Net Sales Ratio
Revenue	ROE	Revenue 1-Year Growth
ROA	Total Assets	

Table 2: Financial Control Variables

2) ***AI Variables***

For our regression analysis, we utilized the 14 count variables, assessing how many times they were used by each company, including AI Engagement, Machine Learning, Image and Pattern Recognition, Language and Text Understanding, Knowledge and Expert Systems, Other Methods, Products and Services, Process Automation, Client Interaction, Data Analytics, Other Areas, In-House Development, Developed by Others or Acquired, and Mixed Development.

3.1.3 Data Collection

We conducted a targeted sample selection of the German market. This includes all companies listed in the DAX, MDAX, and SDAX indices. A total of 160 firms were included: 40 large-cap companies from the DAX, 50 mid-cap companies from the MDAX, and 70 small-cap companies from the SDAX. This comprehensive selection allows us to analyze patterns of AI adoption across a variety of company sizes and industries within the German market.

The period under study extends from 2017 to 2023, a seven-year timeframe that is considered critical for the development and proliferation of AI technologies. This period covers both the initial wave of AI implementation (2017-2019) and the subsequent phase of stabilization and maturation (2020-2023). (Chui et al. 2023)

Our data collection methodology was twofold:

1) ***Financial Control Variables***

We extracted key financial variables from Bloomberg for each year of the study period. These financial data enabled us to calculate Tobin’s Q and other financial metrics annually for each company.

2) ***AI Variables***

For the data collection of each of the AI variables (s. Chapter 3.1.2), we researched based on reliable financial statements and reports, company press releases, and technology-oriented publications. We developed tailored keywords and search strings for each company to collect relevant information (s. Appendix 2).

This methodology ensures that our research is academically rigorous and practically relevant to the current and future business world. It provides a comprehensive view of the interplay between AI adoption and financial performance in the German market from 2017 to 2023.

3.1.4 Panel Data

With our dataset framework, we construct a panel dataset that consists of multiple observations for the same units recorded across various periods, merging aspects of both cross-sectional and time series data (Brooks 2019).

The challenge of causal inference primarily revolves around unobservables, which is central to panel data's role in addressing these issues. In nonrandomized studies, two types of unobservables complicate parameter identification and estimation: (a) time-invariant unit-specific unobservables, which capture the stable characteristics of units (i.e., unit effects), and (b) time-varying unit-specific unobservables, which reflect temporary and unique influences on units (i.e., disturbances). A panel data approach was chosen in this study since it offers advantages for controlling unobservables and consistently estimating causal parameters. (Halaby 2004)

3.2 Regression Model Delineation

This chapter introduces the fixed and random effects models used in the regression analysis. It also discusses the Hausman Test as a basis for deciding on the most fitting model. Finally, it presents a set of factors that affect model estimate reliability and fitting mitigation strategies used in this work.

3.2.1 Fixed Effects Model

A popular statistical technique for examining panel data is the fixed effects (FE) model. This model helps address time-invariant unobserved heterogeneity. (Brüderl and Ludwig 2014)

Heterogeneity is defined as variations in parameters across multiple dimensions, including individuals and time, allowing these variations to be correlated with the regressors (Neal 2018).

A fixed model helps with heterogeneity since it skews causal estimates in conventional regression models. The FE model offers more accurate estimates of the impact of time-varying predictors by accounting for unit-specific features that do not change over time. The fundamental FE model is stated as follows:

$$y_{it} = x_{it}\beta + \alpha_i + \epsilon_{it}$$

Here, y_{it} represents the outcome for unit i at time t, x_{it} is a vector of time-varying covariates, β is the vector of coefficients to be estimated, α_i captures all time-invariant unit-specific characteristics, and ϵ_{it} is the idiosyncratic error term. The key assumption of the FE model is that α_i while potentially correlated with the regressors, remains fixed over time. Thus, it can be eliminated by the so called within-transformation. This transformation subtracts the mean of each variable for each unit, removing the influence of α_i since $\alpha_i = \overline{\alpha_\iota}$.

$$y_{it} - \overline{y_\iota} = (x_{it} - \overline{x_\iota})\beta + (\alpha_i - \overline{\alpha_\iota}) + (\epsilon_{it} - \overline{\epsilon_\iota})$$

This can be simplified to:

$$\widetilde{y_{\iota t}} = \widetilde{x_{\iota t}}\beta + \widetilde{\varepsilon_{\iota t}}$$

$$where\ (\widetilde{\mathrm{y}_{\mathrm{it}}} = \mathrm{y}_{\mathrm{it}} - \overline{\mathrm{y}_\mathrm{i}}), (\widetilde{\mathrm{x}_{\mathrm{it}}} = \mathrm{x}_{\mathrm{it}} - \overline{\mathrm{x}_\mathrm{i}}), \text{and } (\widetilde{\varepsilon_{\mathrm{it}}} = \varepsilon_{\mathrm{it}} - \overline{\varepsilon_\mathrm{i}})$$

Consequently, the FE model estimates causal effects by relying solely on the variation within units over time, rather than between units. This approach is particularly robust when unobserved time-invariant characteristics are likely to confound the relationship between predictors and outcomes. (Brüderl and Ludwig 2014)

3.2.2 Random Effects Model

The Random Effects (RE) model is a commonly used method in panel data analysis that addresses unobserved heterogeneity while still allowing for the estimation of the effects of time-invariant variables. Unlike fixed effects models, which eliminate time-invariant characteristics through within-transformations, the RE model operates under the assumption that these unobserved characteristics are not correlated with the explanatory variables. The basic simplified formulation of the random effects model is as follows:

$$y_{it} = \beta_0 + x_{it}\beta + v_i + \epsilon_{it}$$

Here, y_{it} represents the outcome for unit i at time t, β_0 is the intercept, x_{it} is a vector of covariates, β is the vector of coefficients to be estimated, v_i captures the time-invariant unobserved characteristics (random effects), and ϵ_{it} is the idiosyncratic error term.

The key assumption of the RE model is that the random effects v_i are uncorrelated with the covariates x_{it}:

$$E(v_i|x_{it}) = 0$$

This assumption allows the model to include time-invariant variables and leads to more efficient estimates than fixed effects if it holds. However, if this orthogonality condition is violated, the RE estimates become biased and inconsistent. (Brüderl and Ludwig 2014)

3.2.3 Hausman Test

The Hausman test is a fundamental statistical procedure employed to determine whether a fixed or random effects model is more suitable for panel data analysis. The test evaluates whether the unobserved individual-specific effects ($\alpha_{i\,,} v_i$) are correlated with the explanatory variables (x_{it}), a distinction that directly impacts the consistency and efficiency of the estimators. The random effects model assumes that v_i, is uncorrelated with x_{it}, while the fixed effects model permits such correlation of x_{it} and α_i . The Hausman test formally assesses this assumption by comparing the coefficient estimates obtained from the fixed effects ($\hat{\beta}_{FE}$) and random effects ($\hat{\beta}_{RE}$) models. The test statistic is defined as:

$$m = q'[Var(q)]^{-1}q, \quad q = \hat{\beta}_{FE} - \hat{\beta}_{RE}$$

Here, m is the test statistic that quantifies the difference (q) between the two sets of estimates, adjusted for their variances ($Var(q)$). If α_i, respectively v_i, is uncorrelated with $\mathrm{x_{it}}$, both estimators are consistent, leading to a small q and, consequently, a small m. However, if α_i, respectively v_i, is correlated with $\mathrm{x_{it}}$, the random effects estimator becomes inconsistent, and the difference q grows larger, resulting in a higher m. Under the null hypothesis $\mathrm{H_0}$ of no correlation, the statistic m follows a chi-squared (χ^2) distribution with degrees of freedom equal to the number of coefficients being tested. (Amini et al. 2012)

The choice of model depends on the outcome of the test. If H_0 is not rejected, indicating a small m, the random effects model is preferred due to its efficiency and consistency. If H_0 is rejected, signifying a large m, the fixed effects model is chosen, as it provides unbiased estimates by accounting for potential correlation between α_i and $\mathrm{x_{it}}$. By rigorously testing the underlying assumptions about the data, the Hausman test ensures that the selected model aligns with the data's structural properties, enhancing the reliability and validity of the results. (Amini et al. 2012)

3.2.4 Factors Affecting Model Estimate Reliability in Panel Regressions

Several factors affect estimate reliability if they are present in the regression model. Therefore, one needs to develop an understanding of what these factors are and how they might impact the causal relationship inference.

Heteroscedasticity

Heteroscedasticity is defined as a condition in regression models where the variance of the errors is not constant across observations (Klein et al. 2016). The presence of heteroscedasticity leads to inefficient estimates with wrong standard errors thus leading to incorrect inferences (Gelfand 2015).

Serial Correlation

Serial correlation is defined as the correlation between error terms across different time periods in panel data models causing the estimates to be less efficient due to biased standard errors (Drukker 2003). This leads to inconsistent and biased coefficient estimates (Greenwald 1983).

Cross-Sectional Dependency

Cross-sectional dependency is discussed as a situation in panel data analysis where error terms are correlated across different cross-sectional units of observation at a given point in time (Sarafidis and Wansbeek 2012). The occurrence of cross-sectional dependency therefore results in biased statistical inference (Hoechle 2007).

Multicollinearity

Multicollinearity refers to a statistical issue in multiple regression models where two or more predictor variables show a high degree of correlation with each other (Schreiber-Gregory 2017). The presence of multicollinearity leads to incorrect regression results. To assess multicollinearity, the variance inflation factor (VIF) can be computed. In case this factor is ranging from 5 to 10, multicollinearity is present. (J. H. Kim 2019)

Non-normality

Non-normality is a condition where the residuals or error terms in a regression model do not adhere to a normal distribution which might affect the reliability of the coefficient estimates (Zeckhauser and Thompson 1971).

3.2.5 Improving Estimate Reliability

To mitigate the before mentioned factors affecting estimate reliability, the following concepts are applied in this research.

Driscoll-Kraay robust standard errors

The Driscoll-Kraay covariance matrix estimation method provides standard error estimates that are robust to heteroskedasticity, serial correlation, and cross-sectional dependence. This method provides consistent standard error estimates regardless of the structure or strength of these error dependencies enabling a reliable inference. (Driscoll and Kraay 1998)

Central limit theorem

The central limit theorem states that the regression residuals follow a normal distribution when the sample size is large enough (Lambros 2007). This theory later on has been extended to fixed effect panel models (Kuersteiner and Prucha 2013).

4 Analysis of AI Impact on German listed Companies

After establishing the foundation of this study through the theoretical framework and a detailed description of the methodological approach for the empirical analysis, the following chapters present the results of our regression analysis.

The following chapters analyze the findings of 14 regression models organized into four groups. These groups, based on the dataset framework outlined in Chapter 3.1.1, provide a structured approach to understanding the interdependence of AI engagement and firm valuation.

To achieve this, a structured three-level approach was adopted, informed by our theoretical insights and our dataset framework:

Meta Level	**AI Engagement**		
Categories	AI Method	AI Application Areas	AI Development Approach
Sub-Categories	• Machine Learning • Image and Pattern Recognition • Language and Text Understanding • Knowledge and Expert Systems • Other Methods	• Products and Services • Process Automation • Client Interaction • Data Analytics • Other Areas	• In-house Development • Developed by Others or Acquired • Mixed Development

Table **3**: Analysis Framework adopted after Rammer et al. (2022)

Meta Level: At the highest level, AI Engagement is examined from a broad perspective, aiming to understand its general impact on the valuation of German listed companies. This meta-level displays our first regression seeking to explore the impact of any AI Engagement in general on Tobin’s Q.

Category Level: We analyze three distinct categories on the next level, offering a more detailed view of AI engagement and its influence on firm valuation. This level provides deeper insights into the relationship between specific aspects of AI Engagement and valuation.

Subcategory Level: At the most granular level, we focus on 13 subcategories within these groups. Therefore, we conducted the respective 13 regressions to gain a detailed understanding.

The subsequent chapters will analyze the results of our empirical findings from these three levels, starting with an examination of the meta-level findings to understand how AI Engagement, in general, impacts valuation. In the following chapters, we will then take a more detailed approach by exploring the three categories: AI Methods, AI Application Areas, and AI Development Approaches, with each of their respective subcategories. Throughout this analysis, we will maintain a clear connection to the meta-level perspective. This structured approach ensures consistency with the overarching understanding of AI engagement's impact, synthesizing insights from both the meta-level and category levels, within the four chapters to ultimately answer each of our four hypotheses and address our research question.

4.1 The Impact of AI Methods on Firms' Valuation

This chapter delves into the regression results, which aim to test the second hypothesis:

Hypothesis 2: Every Type of AI Method Positively Impacts Tobin's Q.

Building on the general overview of AI engagement, the following parts explore in greater detail the implications of AI engagement for German listed companies. As the first of the three categories analyzed, as outlined in Chapter 3.1.1, we examine how various AI methods (s. Chapter 2.1.2) employed by companies differ in their impact on company valuation.

4.1.1 Dataset Description

Dependent variable and control variables

Tobin's Q remains the dependent variable. In addition, the control variables stay the same for a detailed data description of Tobin's Q and the control variables.

Independent variables – AI Methods

The independent variables comprise five different methods that we consider in our analysis.

	Machine Learning	Image and Pattern Recognition	Language and Text Understanding	Knowledge and Expert Systems	Other Methods
Descriptive Statistics					
Mean	0.10	0.02	0.03	0.01	0.02
Median	0	0	0	0	0
Standard Deviation	0.39	0.19	0.22	0.08	0.14
Excess Kurtosis	43.18	200.91	65.19	135.62	69.69
Skewness	5.65	12.25	7.43	11.69	8.00
Min	0	0	0	0	0
Max	5	4	3	1	2
Range	5	4	3	1	2
Total Observations	1,120	1,120	1,120	1,120	1,120

Table 4: Overview AI Methods Variables

Machine Learning stands out with the highest mean engagement of 0.10 and a maximum value of 5, reflecting its relatively broader adoption compared to the other methods. The skewness of 5.65 and excess kurtosis of 43.18 suggest that while engagement is concentrated at lower levels, there are notable observations of higher utilization. Image and Pattern Recognition, with a mean of 0.02 and a maximum of 4, exhibits even higher excess kurtosis of 200.91 and skewness of 12.25, indicating that engagement is rare looking at the last seven years of all companies but includes a few significant outliers where companies have utilized this method extensively.

Language and Text Understanding shows a slightly higher mean of 0.03, with a maximum of 3 and similar distribution characteristics, as indicated by its excess kurtosis (65.19) and skewness (7.43).

The Knowledge and Expert Systems category, while having the lowest mean engagement of 0.01 and a maximum of 1, still reflects its targeted application in specific cases, as shown by its excess kurtosis (135.62) and skewness (11.69). Lastly, Other Methods have a mean engagement of 0.02 and a maximum of 2, with an excess kurtosis of 69.69 and skewness of 8.00, pointing to a comparable pattern of infrequent but focused use.

These statistics collectively highlight that AI engagement across specific methods is sparse but indicates that while most companies engage minimally, a subset actively leverages AI methods more intensively. This distribution underscores the emerging yet concentrated adoption of AI technologies in the most recent years.

4.1.2 Results Description

This section presents the findings from the regression analyses that examine the influence of various AI methods on Tobin's Q. For the regression analysis, we utilized the five AI engagement methods as outlined in Chapter 3.1.1: Machine Learning, Image and Pattern Recognition, Language and Text Understanding, Knowledge and Expert system and Other Methods. Furthermore, the control variables, as previously described in Chapter 4.1.1, have been applied in the regressions.

The following equations for the fixed and random effects models were applied for the AI method regressions.

Model Equation – Fixed Effects Model

$$Tobin's\ Q_{it} = \beta_1 \cdot AI\ Methods_{it} + \beta_2 \cdot \log(Market\ Cap_{it}) + \beta_3 \cdot EPS_{it} + \beta_4 \cdot PE_{it} + \beta_5 \cdot Debt\ Equity_{it} + \beta_6 \cdot R\&D\ Intensity_{it} + \beta_7 \cdot ROIC_{it} + \beta_8 \cdot GICS\ Sector_{it} + \alpha_i + \epsilon_{it}$$

- i: Indices individual firms,
- t: Indices time,
- a_i: captures unobserved, time-invariant firm-specific effects
- e_{it}: is the unique error term

Model Equation – Random Effects Model

$$Tobin's\ Q_{it} = \beta_0 + \beta_1 \cdot AI\ Methods_{it} + \beta_2 \cdot \log(Market\ Cap_{it}) + \beta_3 \cdot EPS_{it} + \beta_4 \cdot PE_{it} + \beta_5 \cdot Debt\ Equity_{it} + \beta_6 \cdot R\&D\ Intensity_{it} + \beta_7 \cdot ROIC_{it} + \beta_8 \cdot GICS\ Sector_{it} + \nu_i + \epsilon_{it}$$

- i: Indices individual firms.
- t: Indices time.
- ν_i: Unobserved, firm-specific effects that are random and vary across firms but are constant over time.
- ϵ_{it}: The unique error term that varies across firms and time.
- β_0: The intercept in the random effects model.
- β_k: Coefficients for the independent variables (k=1,2,…,8).

After running both the fixed and random effects model, the Hausman tests conducted across the five regressions all indicated a strong preference for fixed effects models over random effects models. Each test produced significant chi-squared values – 238.87 for Machine Learning, 256.72 for Image and Pattern Recognition, 255.11 for Language and Text Understanding, 252.94 for Knowledge and Expert system, and 244.09 for Other Methods – with p-values well below 0.05. In the analysis of AI methods, just as for AI engagement, the fixed effects model proved to be more suitable for continuing with hypothesis testing. This decision was based on clear differences in how well each model fit the data, with the fixed effects models consistently providing a better and more reliable fit. However, since the fixed effects model is used for the following regressions, the GICS Sector variable will be excluded as it is a categorical variable that cannot be displayed in a fixed effects model (s. Chapter 3.2.1).

The results of the panel regressions are presented in the table below:

		Dependent variable: Tobin's Q				
		Machine Learning	**Image and Pattern Recognition**	**Language and Text Understanding**	**Knowledge and Expert System**	**Other Method**
Control Variables	Type of AI Method	**-0.1190******	**-0.3153******	**-0.0085**	**-0.2084***	**-0.3082******
		(0.0270)	*(0.0218)*	*(0.0266)*	*(0.0951)*	*(0.0533)*
	log(MarketCap)	**1.4054******	**1.4152******	**1.4907******	**1.4089******	**1.4032******
		(0.1564)	*(0.1567)*	*(0.1593)*	*(0.1587)*	*(0.1587)*
	EPS	**-0.0463******	**-0.0471******	**-0.0482******	**-0.0480******	**-0.0480******
		(0.0048)	*(0.0053)*	*(0.0057)*	*(0.0054)*	*(0.0054)*
	PE	**0.0003.**	**0.0003.**	**0.0003.**	**0.0002.**	**0.0003.**
		(0.0001)	*(0.0001)*	*(0.0001)*	*(0.0002)*	*(0.0001)*
	Debt-to-Equity	**0.0007****	**0.0007****	**0.0007****	**0.0007****	**0.0007****
		(0.0002)	*(0.0003)*	*(0.0003)*	*(0.0003)*	*(0.0003)*
	R&D Intensity	**-0.0420***	**-0.0420***	**-0.0427***	**-0.0428***	**-0.0408***
		(0.0202)	*(0.0203)*	*(0.0200)*	*(0.0201)*	*(0.0212)*
	ROIC	**0.0224******	**0.0229******	**0.0237******	**0.0237******	**0.0236******
		(0.0057)	*(0.0059)*	*(0.0061)*	*(0.0061)*	*(0.0060)*
	R-Squared	0.36768	0.37022	0.36553	0.36589	0.3673
	Adj R-Squared	0.2273	0.2305	0.2247	0.2252	0.2270
	N (Observations)	761	761	761	761	761

Driscoll-Kraay robust standard errors in parentheses
*p<0.05; **p<0.01;***p<0.001

Table 5: Results AI Methods Regression Models

Results of AI Methods Variables

The results are presented quantitatively to understand the extent to which different AI methods affect firm valuation (Tobin’s Q).

The analysis indicates a negative impact of Machine Learning on Tobin’s Q with a coefficient of -0.1190, which is statistically significant at the 0.001 level. This result suggests that investments in Machine Learning are associated with a decrease in market valuation under the conditions of this study.

Similarly, Image and Pattern Recognition shows a more pronounced negative effect on Tobin’s Q with a coefficient of -0.3153, which is also significant at the 0.001 level. This larger negative coefficient indicates a stronger adverse reaction from the market to these types of AI technologies compared to Machine Learning.

In contrast, Language and Text Understanding exhibit an essentially neutral effect on Tobin’s Q, with a coefficient of -0.0085, which is not statistically significant. This finding suggests that Language and Text Understanding do not substantially influence market valuation one way or the other within the scope of this analysis.

Knowledge and Expert Systems negatively impact Tobin's Q, with a coefficient of -0.2084, significant at the 0.05 level. This indicates a generally negative market response to this type of AI technology, implying a decrease in firm valuation when these systems are employed.

Lastly, the category labeled Other Methods, encompassing less common or emerging AI technologies, shows a significant negative effect on Tobin's Q with a coefficient of -0.3082, significant at the 0.001 level. This substantial negative impact suggests that the market views these newer AI methods unfavorably regarding adding value to the firm.

Each coefficient provides a measure of the impact that the respective AI method has on firm valuation, with all the results here pointing to varying degrees of negative influences. These influences are rigorously quantified through the regression analysis, and the statistical significance associated with each helps in assessing the confidence level of these findings.

Results Control Variables

The results of the financial control variables are similar across all five models: The analysis in Table **5** reveals consistently positive coefficients for log(Market Cap) across all AI methods, ranging from 1.4054 to 1.4152, all significant at the 0.001 level. This robust positive association suggests that larger firms are better positioned to leverage different types of AI technologies no matter which method they use.

Conversely, EPS uniformly exerts a negative influence on Tobin's Q, with coefficients between -0.0482 and -0.0480, which is significant at the 0.001 level. This indicates a trend where higher earnings per share do not correspond with higher market valuations within the context of AI investments.

The analysis of the PE ratio shows coefficients close to zero across all AI methods, lacking statistical significance. This finding implies that the PE ratio does not play a significant role in the valuation of companies making AI investments with any particular method, suggesting that market perceptions of earnings potential may not be influenced by traditional earnings metrics in the context of AI.

Furthermore, the Debt-to-Equity ratio displays a small but consistent positive effect on Tobin's Q, with coefficients around 0.0007, significant at the 0.01 level. Although the effect size is minor, it indicates a slight market preference for firms that use debt in their capital structure.

Additionally, R&D Intensity shows a slight negative correlation with Tobin's Q, with coefficients around -0.0420, significant at the 0.05 level. This suggests that higher R&D Intensity might not be favorably perceived in terms of market valuation, perhaps due to the speculative nature of R&D investments in AI, which may not yield immediate financial returns.

Lastly, ROIC demonstrates a positive correlation with Tobin's Q, with coefficients ranging from 0.0224 to 0.0237, all significant at the 0.001 level. This positive relationship underscores the importance of efficient capital utilization, with the market rewarding firms that demonstrate effective returns on their investments.

Model Fit

The regression analysis (Table **5**) across different AI Methods demonstrates varied effectiveness in explaining Tobin's Q, as evidenced by the R-squared and adjusted R-squared values. The Machine Learning column shows the strongest explanatory power with an R-squared of approximately 0.36768, indicating that about 36.768% of the variance in Tobin's Q can be explained by this model, with an adjusted R-squared of about 0.2273, which adjusts for the number of predictors used, ensuring a balance between model fit and complexity. The R-squared value measures the proportion of variance in Tobin's Q explained by the models' predictors. At the same time, the adjusted R-squared provides a more accurate assessment by adjusting for the number of predictors, which is crucial for comparing models with varying complexities (Miles

2014). Overall, the R-squared of each of the models varies between 0.365 and 0.37 as for the adj. R-square between 0.224 and 0.2305.

Model Diagnostics

In the analysis of the five regression models focusing on different AI methods, it was crucial to address potential issues such as heteroscedasticity, serial correlation, and cross-sectional dependency. We applied the Driscoll-Kraay robust standard errors to manage these concerns, as discussed in Chapter 3.2.5. The significance of the model coefficients indicates that our standard errors are robust, affirming the model's reliability.

Additionally, the normality of residuals is a key assumption in regression analysis that we needed to validate. With 761 observations, our model adheres to the central limit theorem, which helps mitigate concerns regarding the normality of residuals.

Table **6** further demonstrates the robustness of the models:

Variable	VIF	**Variable**	VIF	**Variable**	VIF	**Variable**	VIF	**Variable**	VIF
Machine Learning	1.0267	Image and Pattern Recognition	1.0065	Language and Text Understanding	1.0186	Knowledge and Expert System	1.0035	Other Method	1.0078
log(MarketCap)	1.0670	log(MarketCap)	1.0664	log(MarketCap)	1.0664	log(MarketCap)	1.0657	log(MarketCap)	1.0697
EPS	1.2988	EPS	1.2800	EPS	1.2799	EPS	1.2779	EPS	1.2768
PE	1.0267	PE	1.0268	PE	1.0268	PE	1.0286	PE	1.0268
Debt-to-Equity	1.0466	Debt-to-Equity	1.0388	Debt-to-Equity	1.0507	Debt-to-Equity	1.0388	Debt-to-Equity	1.0388
R&D Intensity	1.0247	R&D Intensity	1.0247	R&D Intensity	1.0268	R&D Intensity	1.0244	R&D Intensity	1.0272
ROIC	1.3230	ROIC	1.3173	ROIC	1.3172	ROIC	1.3130	ROIC	1.3132

Table 6: VIF AI Methods Models

As the VIFs are all close to 1, this indicates that there is no significant issue with multicollinearity among the predictors, ensuring that our model's estimates are stable and reliable. This robust diagnostic setup supports the validity of our findings across the various AI method analyses.

Concluding from our regression analysis results of various AI methods, we have determined that none of these methods positively affect Tobin's Q. Consequently, it appears that regardless of the AI method employed, the impact on a company's valuation tends to be negative as well. Therefore, the AI methods show very similar results to the general AI engagement, underlining furthermore, the robustness of our initial results. Thus, we must also reject our second hypothesis, which stated that every type of AI method would have a positive impact on Tobin's Q. In fact, the contrary is the place, that no matter what AI method a company invests in, they all have a negative effect.

4.1.3 Discussion of AI Methods Results

This chapter builds on the outcomes of the regression models explored in the previous chapter and delves into the specific reasons why various AI Methods negatively affect Tobin's Q. The discussion is framed within a broader theoretical framework described in Chapter 2, thereby enriching our understanding of how diverse AI methods impact market perspectives and, consequently, valuation metrics such as Tobin's Q. Furthermore, this chapter delves into the potential enhancement of these drivers to positively impact Tobin's Q.

Theoretical Implications.

The regression analysis reveals a consistent negative relationship between all examined AI methods and Tobin's Q. These results align with the theoretical framework, outlining how Tobin's Q is influenced – specifically due to the two main mechanisms discussed in Chapter 2.3.2. Collectively, these factors diminish market confidence in these investments. Possible reasons for these findings include substantial implementation costs, operational complexities, and the delayed realization of returns. This subsequent discussion will delve into a more comprehensive understanding of how the overarching mechanisms interfere with each AI method and its impact on Tobin's Q.

For Machine Learning, a likely explanation for its negative relationship to Tobin´s Q is its resource-intensive nature and the challenges larger firms face in integrating it into legacy systems (Nayak and Dutta 2017). The high costs associated with data acquisition and scalable infrastructure increase the asset book value (the denominator of Tobin's Q) - this only occurs when costs are activated. If not, the cost will increase Tobin's Q through mechanism 1 (s. Chapter

2.3.2). On the other hand, the delays in system integration delay the increase in market value (the numerator), which ultimately results in a lower Tobin's Q. This aligns with Bughin et al. (2018) and Yang, Blount, and Amrollahi (2024), who emphasize the financial and technical barriers, including the need for large datasets, scalable infrastructure, and frequent model updates. These resource-demands likely increase perceived risk among investors, who may see significant upfront costs without immediate value creation. Furthermore, this is consistent with Alekseeva et al. (2021) who identify organizational inaction in large firms as a factor delaying the realization of returns.

For Image and Pattern Recognition, the pronounced negative effect can be attributed to its limited applicability across industries and the significant ethical and regulatory hurdles it faces as mentioned in Chapter 2.1.2. Investments in industries with tight privacy regulations, such as healthcare, result in greater initial costs and potential increase in the asset book value; but this increase occurs only if costs are capitalized. However, due to legal limits, investors do not expect the company's forecasts to be fully achieved. As a result, the market value does not increase in proportion to the book value, which reduces Tobin's Q. (Paolanti and Frontoni 2020) This aligns with Davenport and Kalakota (2019), who highlight challenges in healthcare due to GDPR[3]. Additionally, this observation is supported by R. Li (2019), who discusses privacy risks and compliance costs as critical barriers to adoption. These constraints likely lead investors to perceive companies adopting Image and Pattern Recognition as riskier due to high implementation costs and niche applications.

The negative coefficient for Knowledge and Expert Systems might stem from their narrow focus, which limits adaptability in dynamic environments and the high maintenance costs

[3] General Data Protection Regulation

associated with updating knowledge bases. If capitalized, the continuous costs for system updates increase the asset book value without immediately enhancing the market value, thereby lowering Tobin's Q. (Kaur, Rekhi, and Nayyar 2013) This finding aligns with Abu-Nasser (2017), who highlights that Expert Systems excel in structured tasks but are less effective in flexible, fast-changing environments. Additionally, it reflects the challenges noted by Yang, Blount, and Amrollahi (2024) regarding the integration of these systems into broader operational contexts in large firms. However, it contrasts with Na et al. (2023), who find that larger firms investing in training and employee education enhance the perceived ease of use and usefulness of such technologies, suggesting a potential for mitigating these limitations.

The negative impact of Other Methods is likely explained by their speculative nature, lack of proven use cases, and lack of clear regulatory frameworks. This finding aligns with Cockburn, Henderson, and Stern (2018), who highlight the inherited limitations and risks of hybrid systems. These uncertainties likely increase perceived risks for investors, who may struggle to find immediate applications for experimental technologies. However, this contrasts with Brynjolfsson and McAfee (2017), who argue that these methods hold significant long-term innovation potential, suggesting a gap in reconciling short-term skepticism with long-term strategic value.

In summary, the negative effects of AI Methods on Tobin’s Q are likely due to the difficulty companies face in aligning AI adoption strategies with their operational realities and the market's perception of these investments as high-risk. These findings align with studies like Bughin et al. (2018) and Davenport and Kalakota (2019), while partially contrasting with more optimistic perspectives, such as those from Brynjolfsson and McAfee (2017), on AI’s long-term benefits. Our research contributes by highlighting how the immediate challenges and uncertainties associated with AI adoption outweigh its perceived short-term benefits in the context of large German stock companies.

Practical Implications

The negative correlation between AI engagement, as described in Chapter 4.1 and further substantiated by the negative correlations of the subcategories under AI Methods, has practical implications. This subsequent section will provide a comprehensive analysis of the practical implications of diverse AI methods in light of the previously investigated mechanisms. Ultimately, identifying how AI methods can potentially enhance Tobin’s Q through specific strategic and operational measures.

In the theoretical implications of Machine Learning, it was argued that the negative impact on Tobin's Q might stem from its resource-intensive nature, integration issues, and significant upfront costs for scalable infrastructure and data acquisition (Bughin et al. 2018; Yang, Blount, and Amrollahi 2024). Thus, the practical implications are as follows: (Williamson and Babcock 2020) recommend that companies use financial planning to effectively manage substantial initial investments, ensuring alignment with anticipated long-term returns. This can help organizations avoid a sharp decrease in Tobin's Q by managing asset growth without corresponding immediate increases in market value. Averineni et al. (2024) reinforce these implications by emphasizing the importance of incorporating predictive analytics into business strategy to address the challenges of market volatility and resource optimization for Machine Learning. Organizations can gain actionable insights by systematically integrating Machine Learning models, allowing them to adapt incrementally while reducing the financial burden of large-scale investments. This is consistent with Daiya (2024) emphasis on risk assessment and realistic timelines, as well as Blackburn et al´s. (2020) recommendation for phased investments that ensure measurable contributions to business outcomes and incremental improvements to Tobin's Q.

Key reasons highlighted for Image and Pattern Recognition include its restricted use across different industries, especially in healthcare, along with substantial ethical and regulatory challenges that increase compliance costs and hinder scalability. (Davenport and Kalakota 2019; R. Li 2019). As previously stated by Zhang, Bai, and Ma (2022), effective communication can help align investors' expectations with the company's strategic vision, stabilizing Tobin's Q during the transition phase of Image and Pattern recognition adoption. Furthermore, strict regulatory frameworks must be complied with. Aldoseri, Al-Khalifa, and Hamouda (2023) discuss the importance of making AI systems interpretable and transparent, particularly in compliance and risk-management scenarios. This ensures compliance, increases the reliability and market value of investments in Image and Pattern Recognition technologies, and, ultimately, improves Tobin's Q. However, compliance costs associated with Image and Pattern Recognition can also be lowered. According to (Christiaanse and Hulstijn 2024) the use of automated controls can reduce those costs by effectively preventing misrepresentations and enhancing the detection of mismatches in data or processes. These controls, which are directly integrated into business processes, reduce audit fees and overall compliance costs by ensuring regulatory compliance from the start. This approach not only simplifies compliance, but it also increases the reliability and efficiency of compliance processes.

As previously emphasized, Knowledge and Expert Systems require ongoing updates and maintenance to keep their effectiveness. This requirement results in higher maintenance expenses, which then can increase the denominator of Tobin's Q. (Kaur, Rekhi, and Nayyar 2013; Abu-Nasser 2017) As a result, these systems must be integrated with existing business processes to ensure they provide clear operational benefits and are up to date. Koehler (2018) emphasizes this, arguing that companies must prioritize integration to ensure that AI provides tangible operational benefits and is not redundant. This integration enables companies to use the structured capabilities of Knowledge and Expert Systems to improve operational efficiency, thereby gradually improving Tobin's Q. Furthermore, improving the adaptability of Knowledge and Expert Systems can make them more flexible and capable of handling diverse and evolving tasks, increasing their utility and lowering maintenance costs in the long term. (Engel and Reich 2015) Such strategic investments in technology maintenance and adaptability can improve the operational effectiveness of Knowledge and Expert Systems and help to gradually improve Tobin's Q by aligning the technology more closely with changing business needs and market conditions.

The use of Other Methods, such as those in the early stages of development or with untested use cases, necessitates a strategic approach to pilot programs and risk management. Blackburn et al. (2020) advocate for the use of pilot programs that allow businesses to experiment in controlled environments, reducing concerns about technical feasibility and commercial viability. These early iterations enable businesses to reduce transaction costs by focusing on targeted learning and specific problem-solving, both critical for learning-by-searching and learning-by-doing processes. Furthermore, Mollura et al. (2020) argue that knowledge spillovers from such pilots can significantly boost adoption rates by reducing uncertainty about long-term viability and encouraging broader adoption.

Concluding, companies can potentially enhance financial metrics like Tobin’s Q by strategically integrating AI methods into business operations. This alignment involves strategic financial planning, technological innovation, and strategic business decisions.

5 Conclusion

After reviewing our findings and their implications, this chapter presents the final conclusions of our study. We summarize the main insights into how general AI engagement, as well as the defined subcategories, influence the valuation of German listed companies. In doing so, we connect theoretically established concepts with our empirical real-world observations. Furthermore, we discuss the limitations of our work, noting how certain factors might influence how the results should be interpreted. Finally, we look at possible directions for future research, building on the groundwork laid throughout this study and guiding further efforts to understand the role of AI in shaping a firms' value.

5.1 Summary of Study

This thesis critically assessed the impact of AI engagement on firm valuation, as operationalized through Tobin's Q. It employed a dataset that combined financial metrics from Bloomberg with extensive and structured research into the AI engagement of German listed companies. Our database served as the basis for a detailed regression analysis. Despite the theoretical promise of AI, our empirical findings indicate that the expected positive impacts on Tobin's Q are not currently evident.

This study further examined AI engagement across multiple dimensions—including AI types, application areas, and development approaches—to yield a more nuanced understanding. However, no significant positive impact on Tobin's Q was found across any of these categories. Indeed, none of the examined subcategories showed a positive correlation; most exhibited a negative effect, with only a few demonstrating a neutral influence. These findings suggest that the market, including investors, currently undervalues firms engaged in AI. Two primary factors appear to drive this undervaluation: investors' skepticism regarding future financial returns, and the high initial costs of AI initiatives that may not pay off in the near term. Consequently, the anticipated valuation benefits of AI technologies have not yet materialized.

5.2 Limitations and Need for Further Research

Our study provides valuable insights into answering our initial research question of how AI engagement impacts the valuation of German listed companies. However, it is important to acknowledge several limitations that may affect the interpretation and generalizability of the results.

Tobin's Q approximation

This research uses a simplified version of Tobin's Q, as explained in section 2.2.2. Therefore, our conclusions only apply to this simpler variable. Future studies should calculate Tobin's Q with the market value of debt and the replacement value of assets included to see if the results presented in this research stay consistent.

Data Collection Method

The data was collected through extensive keyword research to identify relevant company news about their AI engagement. However, not all companies disclose such information, implying that some observations might not have been captured by the keyword search. Future studies could address this limitation by incorporating questionnaires or interviews with companies to improve the accuracy of capturing relevant observations.

Data Accuracy and Restraints

The data available has missing variable observations for some companies, as detailed in the data descriptives. This issue limits the dataset to a smaller number of observations. Future studies could improve this by including more databases, thus expanding the sample size.

Additionally, the sample includes a wide variety of companies across three different indices, resulting in a broad range of variable values and the presence of outliers. AI adoption has also been increasing in recent years, which adds skewness to the data. Future research could mitigate these issues by focusing on a single index and narrowing the time frames to periods with more consistent levels of AI adoption.

Model fit

Even though the models include control variables from our dataset that have the strongest explanatory power, the fit of the models are still moderate, with an average R-squared of about 0.36 and an average adjusted R-squared of about 0.22. Future research should aim to enhance the current model by adding more variables that have strong explanatory power. This could improve the model's fit and provide a deeper understanding of the factors influencing Tobin's Q in the context of AI engagement.

Causality versus Correlation

Using regression analysis, the study finds links between artificial intelligence involvement and financial performance but does not prove causality since other intervening factors, such as market dynamics, company-specific strategic decisions may affect the outcomes. Understanding the results and their implications on corporate strategies depends on that distinction.

Mechanisms of AI's influence on Tobin's Q

The derived mechanisms applied in this study were conceptualized to serve as a causal chain to understand AI's impact on Tobin's Q. Following research should further validate or challenge the found mechanisms deepen the understanding of this chain of interactions.

General implications

The theoretical and practical implications found in this study are general implications that have been brought into the context of German companies. Future research could verify these implications by diving into more Germany specific reasons, such as regulations (GDPR) to deepen the understanding of how the German AI setup impacts the engagement.

5.3 Outlook

The aim of this thesis was to examine the relationship between AI engagement and Tobin's Q, beginning with an initial exploration. This examination sets the stage for future, more detailed research into the dynamics of this relationship. It is recommended that further studies concentrate on the causal chains linked to the individual (sub)categories of AI engagement. Such insights can then be translated into actionable strategies for organizations.

Moreover, based on this study, if companies improve their communication to clearly explain the capabilities and limitations of AI with the public markets, it could enable investors to integrate this information into their valuation process, resulting in less skepticism and more accurate assessments of company value. This could lead to a positive benefit on Tobin's Q. Moreover, understanding the expected AI impact, combined with the insights from this thesis, may enhance market opportunity identification. Despite AI engagement currently reducing Tobin's Q, its potential positive impact in the future could reveal currently unrecognized future value.

In addition, extending this research globally could evaluate the generalizability of these findings, potentially tailoring them to the complexities of international markets as well as different company sizes not considered in this study, such as SMEs.

Lastly, in a broader context, AI remains largely in its adoption phase within many enterprises. While our analysis took a retrospective approach by examining past financial metrics, it also incorporated the expectations that investors factor into a firm's valuation. Building on this, we suggested potential pathways for how the full benefits of AI might materialize as companies move beyond initial implementation stages and as the technology matures. As AI becomes more sophisticated, its true impact on valuation metrics may become more pronounced. For this, it is important for firms to stay ahead of the curve in utilizing and optimizing AI outputs to create a competitive advantage and to gain positive investor sentiment – a driver of boosting Tobin's Q

These developments may alter the impact on Tobin's Q. Consequently, we recommend that the implications of this study should be reassessed in the near future.

Overall, this study has begun to explore how AI might impact valuation, highlighting the necessity for more detailed research in future studies building on this fundamental approach.

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Appendices

Appendix 1 – AI Engagement Research Keywords... XXIX

Appendix 2 – R Code for Regression Analysis... XXX

Appendix 1 – AI Engagement Research Keywords

Category	Keyword ("COMPANY” to be replaced with actual firm name)
General AI Keywords	COMPANY artificial intelligence
	COMPANY AI
	COMPANY künstliche intelligenz
	COMPANY KI
	COMPANY AI strategy
	COMPANY AI investments
	COMPANY AI initiative
AI Methods	COMPANY machine learning
	COMPANY image recognition
	COMPANY language processing
	COMPANY expert systems
AI Application Areas	COMPANY AI products
	COMPANY AI Produkte
	COMPANY AI process automation
	COMPANY AI client interaction
	COMPANY AI data analytics
	COMPANY AI services
AI Development Approach	COMPANY AI in-house
	COMPANY AI acquisition
	COMPANY AI partnership
	COMPANY AI collaborative

Appendix 2 – R Code for Regression Analysis

```
#Install needed packages

install.packages("car")

install.packages("lmtest")

install.packages("MASS")

install.packages("readxl")

install.packages("dplyr")

install.packages("estimatr")

install.packages("nlme")

install.packages("sandwich")

install.packages("tidyr")

install.packages("plm")

install.packages("DescTools")

install.packages("e1071")


#libraries

library(car)

library(lmtest)

library(MASS)

library(readxl)

library(dplyr)

library(estimatr)
```

Group Part

```
library(nlme)

library(sandwich)

library(tidyr)

library(plm)

library(DescTools)

library(e1071)


#Data loading

data <- read_excel("/Users/flo/Library/CloudStorage/Dropbox/Studium/NOVA/MA/Panel Data/TQNEW_Panel Regression Data_Final.xlsx", sheet = "Regression Data")



#Clean column names

colnames(data) <- gsub("\\s+|\\r|\\n", "", colnames(data))



#Transformation of numeric variables and factorization of Sectors

data <- data %>%

  mutate(across(-c(Ticker, Name, GICSIndName, GICSSector), as.numeric))


data <- data %>%

  mutate(across(c(GICSIndName, GICSSector), as.factor))
```

```
#Creation of a data frame for panel regression by splitting variables into columns with extra
year column
data_long <- pivot_longer(data,
cols = starts_with(c( "ROIC", "TobinsQRatio", "PE", "MarketCap", "Revenue",
"ROA", "EPS", "R&DNetSales", "ROE", "TotAssets", "TotalLiab", "DebtEquity",
"EPS1YrGr", "EBITDAtoNetSales", "Rev1YrGr", "AIEngagement", "MachineLearning",
"Imagepatternrecognition", "Languagetextunderstanding", "Knowledgeexpertsystem",
"OtherMethod", "Productsservices", "Automationofprocesses", "Interactionwithclients",
"Dataanalytics", "OtherArea", "Developedinhouse", "Developedbyothersacquisition",
"Mixeddevelopment"
)), # Specify variable columns to transform
names_to = c("variable", "year"), names_sep = "_", values_to = "value" )

data_long <- pivot_wider(data_long,names_from = variable, values_from = value)



#Cleaning of NA values
data_clean <- na.omit(data_long)

#Creation of panel data frames
panel_data <- pdata.frame(data_long, index = c("Name", "year"))
panel_data_clean <- pdata.frame(data_clean, index = c("Name", "year"))
```

```
##### DATA DESCRIPTION ####

# This section explores the variables by retrieving the variable descriptives


##Dependent variable

summary(panel_data$TobinsQRatio)

sd(panel_data$TobinsQRatio, na.rm = TRUE) #standard deviation

skewness(panel_data$TobinsQRatio, na.rm = TRUE) #skewnesss

kurtosis(panel_data$TobinsQRatio, type = 2, na.rm = TRUE) #kurtosis

sum(!is.na(panel_data$TobinsQRatio)) # number of observations


##Control Variables subset

subset_data_control <- panel_data %>%

  select(MarketCap, EPS, PE, DebtEquity, R.DNetSales, ROIC)


#Market Capitalization

summary(subset_data_control$MarketCap)

sd(subset_data_control$MarketCap, na.rm = TRUE)

var(subset_data_control$MarketCap, na.rm = TRUE)

skewness(panel_data$MarketCap, na.rm = TRUE)

kurtosis(subset_data_control$MarketCap, type = 2, na.rm = TRUE)

sum(!is.na(subset_data_control$MarketCap)) #number of observations
```

```
#Earnings-per-Share

sd(subset_data_control$EPS, na.rm = TRUE)

var(subset_data_control$EPS, na.rm = TRUE)

skewness(panel_data$EPS, na.rm = TRUE)

kurtosis(subset_data_control$EPS, type = 2, na.rm = TRUE)

sum(!is.na(subset_data_control$EPS)) #number of observations


#Price-to-Earnings

sd(subset_data_control$PE, na.rm = TRUE)

var(subset_data_control$PE, na.rm = TRUE)

skewness(panel_data$PE, na.rm = TRUE)

kurtosis(subset_data_control$PE, type = 2, na.rm = TRUE)

sum(!is.na(subset_data_control$PE)) #number of observations


#Debt-to-Equity

sd(subset_data_control$DebtEquity, na.rm = TRUE)

var(subset_data_control$DebtEquity, na.rm = TRUE)

skewness(panel_data$DebtEquity, na.rm = TRUE)

kurtosis(subset_data_control$DebtEquity, type = 2, na.rm = TRUE)

sum(!is.na(subset_data_control$DebtEquity)) #number of observations


#R&D Intensity
```

```
sd(subset_data_control$R.DNetSales, na.rm = TRUE)
var(subset_data_control$R.DNetSales, na.rm = TRUE)
skewness(panel_data$R.DNetSales, na.rm = TRUE)
kurtosis(subset_data_control$R.DNetSales, type = 2, na.rm = TRUE)
sum(!is.na(subset_data_control$R.DNetSales)) #number of observations

#Return on Invested Capital
sd(subset_data_control$ROIC, na.rm = TRUE)
var(subset_data_control$ROIC, na.rm = TRUE)
skewness(panel_data$ROIC, na.rm = TRUE)
kurtosis(subset_data_control$ROIC, type = 2, na.rm = TRUE)
sum(!is.na(subset_data_control$ROIC)) #number of observations

## AI Engagement variables ##

#AI Engagement
summary(panel_data$AIEngagement)
sd(panel_data$AIEngagement, na.rm = TRUE)
skewness(panel_data$AIEngagement, na.rm = TRUE)
kurtosis(panel_data$AIEngagement, type = 2, na.rm = TRUE)

## Methods
#Machine Learning
```

```
summary(panel_data$Machinelearning)
sd(panel_data$Machinelearning, na.rm = TRUE)
skewness(panel_data$Machinelearning, na.rm = TRUE)
kurtosis(panel_data$Machinelearning, type = 2, na.rm = TRUE)

#Image and Pattern Recognition
summary(panel_data$Imagepatternrecognition)
sd(panel_data$Imagepatternrecognition, na.rm = TRUE)
skewness(panel_data$Imagepatternrecognition, na.rm = TRUE)
kurtosis(panel_data$Imagepatternrecognition, type = 2, na.rm = TRUE)

#Language and Text Understanding
summary(panel_data$Languagetextunderstanding)
sd(panel_data$Languagetextunderstanding, na.rm = TRUE)
skewness(panel_data$Languagetextunderstanding, na.rm = TRUE)
kurtosis(panel_data$Languagetextunderstanding, type = 2, na.rm = TRUE)

#Knowledge- and Expertsystems
summary(panel_data$Knowledgeexpertsystem)
sd(panel_data$Knowledgeexpertsystem, na.rm = TRUE)
skewness(panel_data$Knowledgeexpertsystem, na.rm = TRUE)
kurtosis(panel_data$Knowledgeexpertsystem, type = 2, na.rm = TRUE)
```

```
#Other Methods
summary(panel_data$OtherMethod)
sd(panel_data$OtherMethod, na.rm = TRUE)
skewness(panel_data$OtherMethod, na.rm = TRUE)
kurtosis(panel_data$OtherMethod, type = 2, na.rm = TRUE)

## Area ##

#Products and Services
summary(panel_data$Productsservices)
sd(panel_data$Productsservices, na.rm = TRUE)
skewness(panel_data$Productsservices, na.rm = TRUE)
kurtosis(panel_data$Productsservices, type = 2, na.rm = TRUE)

#Interaction with Clients
summary(panel_data$Interactionwithclients)
sd(panel_data$Interactionwithclients, na.rm = TRUE)
skewness(panel_data$Interactionwithclients, na.rm = TRUE)
kurtosis(panel_data$Interactionwithclients, type = 2, na.rm = TRUE)

#Automation of Processes
summary(panel_data$Automationofprocesses)
sd(panel_data$Automationofprocesses, na.rm = TRUE)
```

```
skewness(panel_data$Automationofprocesses, na.rm = TRUE)

kurtosis(panel_data$Automationofprocesses, type = 2, na.rm = TRUE)


#Data Analytics

summary(panel_data$Dataanalytics)

sd(panel_data$Dataanalytics, na.rm = TRUE)

skewness(panel_data$Dataanalytics, na.rm = TRUE)

kurtosis(panel_data$Dataanalytics, type = 2, na.rm = TRUE)


#Other Area

summary(panel_data$OtherArea)

sd(panel_data$OtherArea, na.rm = TRUE)

skewness(panel_data$OtherArea, na.rm = TRUE)

kurtosis(panel_data$OtherArea, type = 2, na.rm = TRUE)


## Development Type ##


#Developed Inhouse

summary(panel_data$Developedinhouse)

sd(panel_data$Developedinhouse, na.rm = TRUE)

skewness(panel_data$Developedinhouse, na.rm = TRUE)

kurtosis(panel_data$Developedinhouse, type = 2, na.rm = TRUE)
```

```
#Developed by Others or Acquisition
summary(panel_data$Developedbyothersacquisition)
sd(panel_data$Developedbyothersacquisition, na.rm = TRUE)
skewness(panel_data$Developedbyothersacquisition, na.rm = TRUE)
kurtosis(panel_data$Developedbyothersacquisition, type = 2, na.rm = TRUE)

#Mixed Development
summary(panel_data$Mixeddevelopment)
sd(panel_data$Mixeddevelopment, na.rm = TRUE)
skewness(panel_data$Mixeddevelopment, na.rm = TRUE)
kurtosis(panel_data$Mixeddevelopment, type = 2, na.rm = TRUE)



##### MODELS #####
# In this section, random and fixed effects models are run with a subsequent Hausman Test to test for the most fitting model
# Afterwards, the Driscoll-Kraay covariance matrix estimation method is applied to provide robust standard error estimates
# This is done for AI Engagement as well as each method, application area and development approach

## AI Engagement ##
```

```
random_model_TQ <- plm(TobinsQRatio ~ AIEngagement + log(MarketCap) + EPS + PE+
DebtEquity+ R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")
summary(random_model_TQ)

fixed_model_TQ <- plm(TobinsQRatio ~ AIEngagement+ log(MarketCap) + EPS + PE +
DebtEquity +R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQ)

#Model Test
hausman_test <- phtest(fixed_model_TQ, random_model_TQ)
print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedastic-
ity, and serial correlation)
coeftest(fixed_model_TQ, vcov = vcovSCC(fixed_model_TQ, type = "HC1"))

## AI Methods ##

##Machine Learning
random_model_TQML <- plm(TobinsQRatio ~ Machinelearning + log(MarketCap) + EPS +
PE+ DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")
summary(random_model_TQML)
```

fixed_model_TQML <- plm(TobinsQRatio ~ Machinelearning + log(MarketCap) + EPS + PE + DebtEquity + R.DNetSales + ROIC + GICSSector, data = panel_data, model = "within")

summary(fixed_model_TQML)

#Model Test

hausman_test <- phtest(fixed_model_TQML, random_model_TQML)

print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedasticity, and serial correlation)

coeftest(fixed_model_TQML, vcov = vcovSCC(fixed_model_TQML, type = "HC1"))

##Image and Pattern Recognition

random_model_TQIP <- plm(TobinsQRatio ~ Imagepatternrecognition + log(MarketCap) + EPS + PE + DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")

summary(random_model_TQIP)

fixed_model_TQIP <- plm(TobinsQRatio ~ Imagepatternrecognition + log(MarketCap) + EPS + PE + DebtEquity +R.DNetSales+ ROIC + GICSSector, data = panel_data, model = "within")

summary(fixed_model_TQIP)

```
#Model Test
hausman_test <- phtest(fixed_model_TQIP, random_model_TQIP)
print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedasticity, and serial correlation)
coeftest(fixed_model_TQIP, vcov = vcovSCC(fixed_model_TQIP, type = "HC1"))

##Language and Text Understanding
random_model_TQLT <- plm(TobinsQRatio ~ Languagetextunderstanding +log(MarketCap) + EPS + PE+ DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")
summary(random_model_TQLT)

fixed_model_TQLT <- plm(TobinsQRatio ~ Languagetextunderstanding + log(MarketCap) + EPS +PE  + DebtEquity + R.DNetSales + ROIC + GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQLT)

#Model Test
hausman_test <- phtest(fixed_model_TQLT, random_model_TQLT)
print(hausman_test)
```

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedasticity, and serial correlation)

coeftest(fixed_model_TQLT, vcov = vcovSCC(fixed_model_TQLT, type = "HC1"))

##Knowledgeexpertsystem

random_model_TQEK <- plm(TobinsQRatio ~ Knowledgeexpertsystem + log(MarketCap) + EPS + PE+ DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")

summary(random_model_TQEK)

fixed_model_TQEK <- plm(TobinsQRatio ~ Knowledgeexpertsystem + log(MarketCap) + EPS+ PE +DebtEquity + R.DNetSales + ROIC + GICSSector, data = panel_data, model = "within")

summary(fixed_model_TQEK)

#Model Test

hausman_test <- phtest(fixed_model_TQEK, random_model_TQEK)

print(hausman_test)

#Alternatively, using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedasticity, and serial correlation)

coeftest(fixed_model_TQEK, vcov = vcovSCC(fixed_model_TQEK, type = "HC1"))

```
##OtherMethods
random_model_TQOM <- plm(TobinsQRatio ~ OtherMethod + log(MarketCap) + EPS +
PE+ DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")
summary(random_model_TQOM)

fixed_model_TQOM <- plm(TobinsQRatio ~ OtherMethod + log(MarketCap) + EPS + PE
+DebtEquity + R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQOM)

#Model Test
hausman_test <- phtest(fixed_model_TQOM, random_model_TQOM)
print(hausman_test)

#Alternatively, using Driscoll-Kraay standard errors (robust to cross-sectional dependence,
heteroscedasticity, and serial correlation)
coeftest(fixed_model_TQOM, vcov = vcovSCC(fixed_model_TQOM, type = "HC1"))

### AI Application Areas ##

##Productsservices
```

```
random_model_TQPS <- plm(TobinsQRatio ~ Productsservices + log(MarketCap) + EPS +
PE+ DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model = "random")
summary(random_model_TQPS)

fixed_model_TQPS <- plm(TobinsQRatio ~ Productsservices + log(MarketCap) + EPS + PE
+DebtEquity + R.DNetSales + ROIC + GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQPS)

#Model Test
hausman_test <- phtest(fixed_model_TQPS, random_model_TQPS)
print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedastic-
ity, and serial correlation)
coeftest(fixed_model_TQPS, vcov = vcovSCC(fixed_model_TQPS, type = "HC1"))


##Automation of Processes
random_model_TQAP <- plm(TobinsQRatio ~ Automationofprocesses +log(MarketCap) +
EPS + PE+ DebtEquity +R.DNetSales + ROIC + GICSSector, data = panel_data, model =
"random")
summary(random_model_TQAP)
```

```
fixed_model_TQAP <- plm(TobinsQRatio ~ Automationofprocesses + log(MarketCap) +
EPS + PE +DebtEquity + R.DNetSales + ROIC + GICSSector, data = panel_data, model =
"within")
summary(fixed_model_TQAP)

#Model Test
hausman_test <- phtest(fixed_model_TQAP, random_model_TQAP)
print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedastic-
ity, and serial correlation)
coeftest(fixed_model_TQAP, vcov = vcovSCC(fixed_model_TQAP, type = "HC1"))



##Interaction with Clients
random_model_TQIC <- plm(TobinsQRatio ~ Interactionwithclients + log(MarketCap) +
EPS + PE+ DebtEquity +R.DNetSales + ROIC+ GICSSector, data = panel_data, model =
"random")
summary(random_model_TQIC)

fixed_model_TQIC <- plm(TobinsQRatio ~ Interactionwithclients + log(MarketCap) + EPS +
PE +DebtEquity + R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQIC)
```

```
#Model Test
hausman_test <- phtest(fixed_model_TQIC, random_model_TQIC)
print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedastic-
ity, and serial correlation)
coeftest(fixed_model_TQIC, vcov = vcovSCC(fixed_model_TQIC, type = "HC1"))



##Data Analytics
random_model_TQDA <- plm(TobinsQRatio ~ Dataanalytics + log(MarketCap) + EPS +
PE+ DebtEquity +R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "random")
summary(random_model_TQDA)

fixed_model_TQDA <- plm(TobinsQRatio ~ Dataanalytics + log(MarketCap)  + EPS + PE
+DebtEquity + R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQDA)

#Model Test
hausman_test <- phtest(fixed_model_TQDA, random_model_TQDA)
print(hausman_test)
```

```
#Alternatively, using Driscoll-Kraay standard errors (robust to cross-sectional dependence,
heteroscedasticity, and serial correlation)
coeftest(fixed_model_TQDA, vcov = vcovSCC(fixed_model_TQDA, type = "HC1"))



##Other Area
random_model_TQOA <- plm(TobinsQRatio ~ OtherArea + log(MarketCap) + EPS + PE+
DebtEquity +R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "random")
summary(random_model_TQOA)

fixed_model_TQOA <- plm(TobinsQRatio ~ OtherArea + log(MarketCap) + EPS + PE
+DebtEquity + R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQOA)

#Model Test
hausman_test <- phtest(fixed_model_TQOA, random_model_TQOA)
print(hausman_test)

#Using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedastic-
ity, and serial correlation)
coeftest(fixed_model_TQOA, vcov = vcovSCC(fixed_model_TQOA, type = "HC1"))

### AI Development Approach ##
```

```
##Developedinhouse
random_model_TQDI <- plm(TobinsQRatio ~ Developedinhouse +log(MarketCap) + EPS +
PE+ DebtEquity +R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "random")
summary(random_model_TQDI)

fixed_model_TQDI <- plm(TobinsQRatio ~ Developedinhouse + log(MarketCap) + EPS +
PE +DebtEquity + R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "within")
summary(fixed_model_TQDI)

#Model Test
hausman_test <- phtest(fixed_model_TQDI, random_model_TQDI)
print(hausman_test)

#Alternatively, using Driscoll-Kraay standard errors (robust to cross-sectional dependence,
heteroscedasticity, and serial correlation)
coeftest(fixed_model_TQDI, vcov = vcovSCC(fixed_model_TQDI, type = "HC1"))


##Developedbyothersacquisition
random_model_TQDOA <- plm(TobinsQRatio ~ Developedbyothersacquisition + log(Mar-
ketCap) + EPS + PE+ DebtEquity +R.DNetSales + ROIC+ GICSSector, data = panel_data,
model = "random")
```

summary(random_model_TQDOA)

fixed_model_TQDOA <- plm(TobinsQRatio ~ Developedbyothersacquisition + log(MarketCap) + EPS + PE +DebtEquity + R.DNetSales + ROIC + GICSSector, data = panel_data, model = "within")

summary(fixed_model_TQDOA)

#Model Test

hausman_test <- phtest(fixed_model_TQDOA, random_model_TQDOA)

print(hausman_test)

#Alternatively, using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedasticity, and serial correlation)

coeftest(fixed_model_TQDOA, vcov = vcovSCC(fixed_model_TQDOA, type = "HC1"))

##Mixed Development

random_model_TQMD <- plm(TobinsQRatio ~ Mixeddevelopment + log(MarketCap) + EPS + PE+ DebtEquity +R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "random")

summary(random_model_TQMD)

fixed_model_TQMD <- plm(TobinsQRatio ~ Mixeddevelopment +log(MarketCap) + EPS + PE +DebtEquity + R.DNetSales + ROIC+ GICSSector, data = panel_data, model = "within") summary(fixed_model_TQMD)

#Model Test

hausman_test <- phtest(fixed_model_TQMD, random_model_TQMD)

print(hausman_test)

lternatively, using Driscoll-Kraay standard errors (robust to cross-sectional dependence, heteroscedasticity, and serial correlation)

coeftest(fixed_model_TQMD, vcov = vcovSCC(fixed_model_TQMD, type = "HC1"))

VIFs DIAGNOSTIC

In this section the variance inflation factor (VIF) is computed for each regression (AI engagement, methods, application areas and development approach)

AI Engagement

fixed_model_TQ <- plm(TobinsQRatio ~ AIEngagement+ log(MarketCap) + EPS + PE + DebtEquity +R.DNetSales + ROIC, data = panel_data, model = "within")

summary(fixed_model_TQ)

#Model Diagnostics

transformed_data <- model.matrix(fixed_model_TQ)

ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))

```
vif(ols_model)


## AI Methods ##


##Machine Learning
fixed_model_TQML <- plm(TobinsQRatio ~ Machinelearning + log(MarketCap) + EPS + PE
+ DebtEquity + R.DNetSales + ROIC , data = panel_data, model = "within")
summary(fixed_model_TQML)
#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQML)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)


##Image and Pattern Recognition
fixed_model_TQIP <- plm(TobinsQRatio ~ Imagepatternrecognition + log(MarketCap) +
EPS +  PE  + DebtEquity +R.DNetSales+ ROIC , data = panel_data, model = "within")
summary(fixed_model_TQIP)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQIP)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
```

```
vif(ols_model)


##Language and Text Understanding

fixed_model_TQLT <- plm(TobinsQRatio ~ Languagetextunderstanding + log(MarketCap) +
EPS +PE  + DebtEquity + R.DNetSales + ROIC , data = panel_data, model = "within")

summary(fixed_model_TQLT)


#Model Diagnostics

transformed_data <- model.matrix(fixed_model_TQLT)

ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))

vif(ols_model)


##Knowledge and Expertsystems

fixed_model_TQEK <- plm(TobinsQRatio ~ Knowledgeexpertsystem + log(MarketCap) +
EPS+ PE  +DebtEquity + R.DNetSales +  ROIC , data = panel_data, model = "within")

summary(fixed_model_TQEK)


#Model Diagnostics

transformed_data <- model.matrix(fixed_model_TQEK)

ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))

vif(ols_model)


##Other Methods
```

```
fixed_model_TQOM <- plm(TobinsQRatio ~ OtherMethod + log(MarketCap) + EPS + PE
+DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQOM)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQOM)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)

## AI Application Areas ##

##Products and Services
fixed_model_TQPS <- plm(TobinsQRatio ~ Productsservices + log(MarketCap) + EPS + PE
+DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQPS)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQPS)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)

##Automation of Processes
```

```
fixed_model_TQAP <- plm(TobinsQRatio ~ Automationofprocesses + log(MarketCap) +
EPS + PE +DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQAP)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQAP)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)



##Interaction with Clients
fixed_model_TQIC <- plm(TobinsQRatio ~ Interactionwithclients + log(MarketCap) + EPS +
PE +DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQIC)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQIC)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)



##Data Analytics
```

```
fixed_model_TQDA <- plm(TobinsQRatio ~ Dataanalytics + log(MarketCap)  + EPS + PE
+DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQDA)


#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQDA)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)


##Other Area
fixed_model_TQOA <- plm(TobinsQRatio ~ OtherArea + log(MarketCap) + EPS + PE
+DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQOA)


#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQOA)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)


## AI Development Type ##


##Developed Inhouse
```

```
fixed_model_TQDI <- plm(TobinsQRatio ~ Developedinhouse + log(MarketCap) + EPS +
PE +DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
summary(fixed_model_TQDI)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQDI)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)

##Developed by Others or Acquisition
fixed_model_TQDOA <- plm(TobinsQRatio ~ Developedbyothersacquisition + log(Mar-
ketCap) + EPS + PE +DebtEquity + R.DNetSales + ROIC, data = panel_data, model =
"within")
summary(fixed_model_TQDOA)

#Model Diagnostics
transformed_data <- model.matrix(fixed_model_TQDOA)
ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))
vif(ols_model)

##Mixed Development
fixed_model_TQMD <- plm(TobinsQRatio ~ Mixeddevelopment +log(MarketCap) + EPS +
PE +DebtEquity + R.DNetSales + ROIC, data = panel_data, model = "within")
```

```
summary(fixed_model_TQMD)


#Model Diagnostics

transformed_data <- model.matrix(fixed_model_TQMD)

ols_model <- lm(transformed_data[,1] ~ ., data = as.data.frame(transformed_data))

vif(ols_model)
```