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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON FINANCIAL PERFORMANCE IN THE GERMAN FINANCIAL SERVICE INDUSTRY – A CONTENT ANALYSIS

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Abstract

Artificial Intelligence is one of the main drivers of Industry 4.0. This Master Thesis assesses the impact of mentioning AI-related terms in annual reports on financial performance. By focusing on domestic listed German companies in the financial service industry, this research contributes to understanding the AI-adoption stage. A quantitative research design is applied by reviewing a sample of 84 companies and 323 annual reports over four years. All in all, the findings show a linear increase in mentioning AI-related terms. AI-related terms do not provide sufficient explanatory power of financial performance. However, some evidence exists supporting a positive impact.

Title: The impact of Artificial Intelligence on financial performance in the German financial service industry – A content analysis

Keywords: Artificial Intelligence, Financial performance, Germany, Financial services

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1. Introduction

Artificial Intelligence (AI) is perceived as one of the primary drivers of Industry 4.0 (Brynjolfsson & McAfee, 2017; Zhang, et al., 2018). With the increasing volume of organisational data (Ratia, Myllärniemi, & Helander, 2018), the ubiquitous connectivity (Burgess, 2018), the increase of computing power at a lower price, and technological advancement, AI developed into a business opportunity (Purdy & Daugherty, 2017). This is supported by companies using AI more intensely in their digital transformation strategy, because the technology can generate knowledge and intelligence from existing large datasets (Lichtenthaler, 2020), increasing, for example, the productivity of processes. Either stand-alone or combined, AI techniques can realise different functional applications (Table 1) (WIPO, 2019). Several surveys have been conducted to capture companies' implications, whereas the results show that most businesses recognise the benefit of AI. The reason for that is, inter alia, a positive connection to their financial performance in terms of operational efficiency, revenue, operating cost, and profitability. However, surveys are mostly conducted by consultancy companies, which offer the service of implementing AI-strategies. Through surveys, investors and external stakeholders mostly gain an impression of the industries' AI-adoption stage. It would be beneficial for them to understand whether a company has implemented AI profitably by reviewing published company information, which is the main focus of this research.

To the best of the author's knowledge, this thesis is the first to analyse the impact on financial performance based on a quantitative research design using AI-related terms in annual reports. Firstly, this research assesses whether AI-related terms in annual reports are a sufficient explanatory variable to describe financial performance. Secondly, this research contributes to understanding the AI-adoption stage in the German financial service industry. Through a content analysis of annual reports, a dataset of AI-related terms is created for 84 companies from 2016 to 2019. By analysing seven models, it is found that AI-related terms do not provide explanatory power regarding financial performance in terms of ROA, ROE and P/E. However, some evidence is provided that a positive impact on accounting performance exists. Consequently, future research is needed to analyse the AI-related terms in annual reports for a larger sample of companies and over a more extended period. In addition, further investigation is needed to understand whether AI-related terms reflect the AI-adoption in the respective company. The report is organised according to the following structure: literature review, hypothesis development, methodology, results, discussion and limitations, and conclusion.

2. Literature Review

2.1. Artificial Intelligence - a business case

According to Forbes, AI is expected to contribute to the economy by an additional 1.7% among various industry by 2035. The growth is explained by the potential increase in productivity, facilitating 38% profit gains (Columbus, 2017). In almost all industries, companies implemented AI, whereby McKinsey reports that the high-tech and telecom sector and the financial services industry belong to the top AI adopters (McKinsey, 2017b). According to Accenture, financial service, manufacturing, and information and communication will benefit the most. Among those industries, the financial sector is expected to benefit from AI with an additional USD 1.2tn and an increase in profit by 31% in 2035 (Purdy & Daugherty, 2017).

The impact of AI in most businesses has just started to display (Lichtenthaler, 2020), for example, that the productivity can be improved by increasing the scale and speed of processes (Plastino & Purdy, 2018). In addition to potential cost savings, the quality of the processes could also be enhanced, e.g. in fraud detection (Burgess, 2018). Furthermore, AI drives innovation by offering new services and products, offering new revenue sources (Plastino & Purdy, 2018). A study published in the Harvard Business Review proved that companies that describe themselves as data-driven perform better in operational and financial results based on interviews of 330 public North American companies. By generating knowledge from existing datasets, data-driven companies can make better decisions, enable more accurate predictions, and intervene accordingly. 68% of the companies rated themselves as data-driven based on a scale of five as three or above (McAfee & Brynjolfsson, 2012). In collaboration with BCG, MIT Sloan Management Review also surveyed countries outside the US by involving more than 2,500 senior executives from 29 industries in 97 countries and showed that AI is perceived by 90% of the respondents as a business opportunity. Still, 70% have recognised minimal or no impact of AI implementation. Of the companies that significantly invested in AI, 60% noted a business gain. The research also found that 72% of companies using AI to generate revenue expected continuing success in the next five years, while among those companies that focus on implementing AI to cut cost, only 44% anticipated success (Ransbotham S. , Khodabandeh, Fehling, LaFountain, & Kiron, 2019). In general, companies, which only started to implement AI, focus on reducing cost, and as they gain experience, the objective is shifted towards growth potential (McKinsey, 2017b). An earlier survey, including 3,000 executives in 14 industries and ten countries concluded that 20% of the companies used AI at scale or in core businesses, e.g. financial service companies apply AI in customer services. Companies that adopted AI showed a higher profit margin, and it is anticipated that the benefit will increase going forward (McKinsey, 2017b). McKinsey conducted a similar global study in 2019, which showed that companies increasingly implemented AI technologies in several processes. 58% of the companies used at least one AI functionality compared to 47% in 2018. Moreover, 30% adopted AI in multiple business activities compared to 21% in 2018. On average, companies applied AI in three processes, while AI high performers[1] used AI on average in 11 cases. Going forward, 3/4 of respondents, which plan or have adopted AI, will further invest in AI in the next three years. Regarding financial performance, 63% of businesses mentioned additional revenue generation and 44% reported a cost reduction in the business activity AI was implemented

[1] Companies implementing AI in five or more activities (High Performers are 3 % of all companies using AI)

(McKinsey, 2019). In 2019, 1/5 of respondents recognised that AI contributed to more than 5% of their EBIT (McKinsey, 2020).

2.2. Artificial Intelligence in the financial service industry

The implementation of AI is a significant part of the financial service sector's transformation (Met, Kabukçu, Uzunoğulları, Soyalp, & Dakdevir, 2020), which is evident as financial services is one of the leading investors in AI (van der Burgt, 2019). In this sector, it is a common approach that specific objectives are set, and only a defined number of action parameters exist due to the regulatory system. In combination with the high volume of data and typical recurring tasks, AI can outperform initial processes (Zetzsche, Arner, Buckley, & Tang, 2020).

McKinsey showed that in 2019 62% of the financial services companies reported having implemented at least one AI technology. AI applications that are mentioned frequently are Robotic Process Automation (36%), virtual agents (32%), natural language text understanding (28%), machine learning (25%), and computer vision (24%) (McKinsey, 2019). A survey addressing the DACH region found that in the financial industry, companies implemented AI with the following objectives: efficiency improvements, cost reductions, personalisation through Chatbots, and compliance with regulations (PwC, 2020). Companies apply AI in Customer Services, Operations and Risk, Trading and Portfolio Management, Regulatory compliance and supervision, Payments and Infrastructure, and Data security and monetisation (Table 2) whereby, Risk Management is perceived as one of the most promising AI implementation fields (Ryll, et al., 2020). Robotic Process Automation (RPA) represents one possibility to implement intelligent automation (Ratia, Myllärniemi, & Helander, 2018). A use case for increasing efficiencies is Santander Consumer Bank, which implemented RPA and estimated to save more than 30,000 hours in 2019 (Automationanywhere, 2020). In general, RPA can facilitate 25% to 50% cost savings (ATKearney, 2016). In a global study in the finance sector, 51% of respondents indicated a slight increase and 18% a significant increase in profitability due to AI implementation. The impact can be differentiated between FinTechs and incumbents. FinTechs focus on creating new revenue streams by developing new AI products and services, while incumbents focus on improving existing processes. Consequently, a difference in companies reporting a significant profitability growth exists between incumbents (7%) and Fintechs (30%) (Ryll, et al., 2020). Königstorfer & Stefan Thalmann (2020) conducted a literature review of AI application in commercial banks for 2009-2019 and suggested that AI can be applied to all core business areas. They recognised cost reduction in lending and security, compliance improvements, and new revenue generation through customer targeting and new types of services. Case studies in the financial service industry estimated a revenue increase larger than 10% due to AI implementation (Wamba-Taguimdje, Wamba, Kamdjoug, & Wanko, 2020). Despite the benefit, only 40% of financial service companies allocated more than 10% of their R&D budget to AI (Ryll, et al., 2020).

2.3. Artificial Intelligence in Germany

In Europe, Germany has the highest number of AI-related patent applications (WIPO, 2019), and announced EUR 3bn government investments in AI R&D in 2018 (Perrault, et al., 2019). Comparable with the US, at least 30% of tasks in 62% of jobs can be automated with AI in Germany (McKinsey, 2017a). It is estimated that AI implementation can impact the Gross Domestic Product (GDP) by an additional 11.3% in 2030, translated into EUR 430bn. The economic impact is mainly explained by AI adoption in consumption-side product enhancements. From a consumer perspective, AI can increase products' value through improved quality, more personalised offers, and fewer consumer required tasks (PwC, 2018). Besides all the previously mentioned benefits, almost half of 500 surveyed companies perceived AI as not relevant. Nevertheless, the positive perception may depend on the company's size, as businesses, which recognised the benefit of AI, tend to have more than 500 employees (83%), and generate up to EUR 1bn annual revenue (72%). Companies that were not adopting AI point out to the location disadvantage due to high scepticism towards AI and low governmental AI investments. Among the businesses that implemented AI, 70% used it for data analysis in decision-making, and 63% applied AI to automate existing processes, with a total RPA adoption rate of 39% (PwC, 2019). The increase in productivity is perceived as a significant benefit for 47% of 555 companies (Berg, 2019). Similar to the financial service's global context, German companies are experienced with AI, and the potential for high returns on AI investment exists (PwC, 2019). In the German finance and insurance industry, 44% of tasks can be automated (McKinsey, 2017a). However, the financial service industry in Germany is at an early stage of AI adoption piloting small scale AI projects. Although financial service companies perceive AI as relevant, the technology is not yet used widely (PwC, 2020). Another study, including 130 executives of German financial institutions, showed that 22% of companies used AI in daily operations. Yet, none of the executives stated that they have a defined and fully implemented AI strategy (EGC Eurogroup Consulting, 2019).

2.4. Limitations to the impact of Artificial Intelligence

Researchers are also concerned about the realisation of the mentioned advantages (Königstorfer & Thalmann, 2020). The benefit of AI implementation cannot be anticipated automatically and immediately. This is supported by BCG reporting that 65% of companies invested in AI in recent years have not yet recognised its value. For more AI experienced businesses, it is 30% (Ransbotham S. , Khodabandeh, Fehling, LaFountain, & Kiron, 2019). Factors that can impact the success of AI implementation are company culture, quality of existing data, top management leadership, talent management, and technology. The company culture needs to adopt a data-driven focus (Pugna, Dutescu, & Stanila, 2019). In fact, data-driven companies stated that they had outperformed their business objectives twice as likely as companies not embedding a data-driven culture (Smith, Stiller, Guszcza, & Davenport, 2019). Nevertheless, some businesses still decide based on intuition, often seen as the highest-paid person's opinion, not on insights generated by data analytics (McAfee & Brynjolfsson, 2012). The importance of data quality is pointed out by 69% of German companies (PwC, 2019), because the use of biased data to train the model, would also result in a biased outcome (Burgess, 2018). Companies embedding their AI strategy within the business strategy also recognised a higher impact on their financials (McKinsey, 2019). Moreover, 50% of companies that invested in high-risk AI projects reported value creation from AI (Ransbotham S. , Khodabandeh, Fehling, LaFountain, & Kiron, 2019). According to the MIT Sloan Management review, the probability of obtaining significant financial advantages increases by 34% if companies focus on organisational learning. This means that multiple interactions between humans and AI applications should be facilitated to grow a collective knowledge (Ransbotham S. , et al., 2020).

3. Hypothesis development

The Artificial Intelligence Index Report 2019 refers to the relevance of analysing firm-level data of AI-implementation to understand the impact on firms performance (Perrault, et al., 2019). As mentioned in the literature review, surveys measured the impact of AI on revenue, operating cost, and profitability. Among others, Reis et al. (2020) proved the positive impact of Machine Learning on financial performance in terms of EBIT, ROI, and ROS through a survey, within large European and North American companies. Besides surveys, the AI Index Report 2019 showed companies' perception of AI by referring to an analysis of AI-related terms mentioned on earnings calls for 3,000 publicly traded companies in the US. Terms included were AI, Big Data, Cloud, and Machine Learning. The total number of mentioned terms grew from 2016 to 2018 by 390%. In the period including 2018 and Q1 of 2019, the terms are mostly mentioned in the finance sector (Perrault, et al., 2019). Hence it is reviewed whether similar developments are recognised in Germany.

Hypothesis H1a: German domestic listed companies in the financial service sector show an increase in mentioning AI-related terms in their annual report from 2016 to 2019.

Hypothesis H1b: Companies, which mentioned AI-related terms in their annual report, show a higher financial performance compared to other companies.

The literature differentiates between companies that apply AI in some processes and AI high performers implementing AI on average in 11 activities. AI high performers recognise a financial benefit in terms of increased revenue and decreased costs by at least 5% (McKinsey, 2019). It is assumed that AI high performers mention AI-related terms more often than their peers as the technology is part of their business strategy.

Hypothesis H1c: The frequency of mentioning AI-related terms in companies' annual reports impacts financial performance. Companies, which mentioned AI more often, perform better than other companies.

In financial services, proactive AI adopters report a 10% higher profit margin[2] than the industry average. Companies in the same sector, which are in the early stage or have not implemented AI, show a lower than average industry profit margin (McKinsey, 2017b). Therefore, it is assumed that early adopters mentioned AI-related terms in 2016 already and have more experience by mentioning AI-related terms also in the following years.

Hypothesis H2: Early adopters of AI show a higher financial performance compared to companies implementing AI recently.

Big Data and Cloud computing are often applied in combination with AI. Cloud computing offers the required storage and computing power needed to adopt AI capabilities. Big Data supports companies with information, and in combination with AI, more significant business insights can be generated (Ryll, et al., 2020). Hence, it is investigated whether companies perceive the three technologies as equivalent relevant or instead focus on one.

Hypothesis H3: Big Data, Cloud, and AI-related terms are likely to be mentioned in the same annual report.

[2] Continuing operational before exceptional items profit divided by revenue

It is assumed that companies, which mentioned more specific terms, also have a deeper understanding of the technology than companies mentioning more general terms. Therefore, it is anticipated that companies mentioning more specific terms are more likely to have implemented AI, and therefore financial benefits are recognised. Specific AI keywords include RPA, Machine Learning and Chatbots. Generic keywords are AI, Advanced Analytics, and Industry4.0.

Hypothesis H4: The mentioning of different keywords in the annual report impacts financial performance. Mentioning more specific AI-related terms shows an increased financial performance compared to more generic keywords.

In this research, listed companies are chosen as requirements regarding their public disclosure exist, resulting in a high degree of credibility (Chakroun, Matoussi, & Mbirki, 2016). Financial Statements and the Management reports must be complete, correct (Bundesministerium der Justiz und für Verbraucherschutz (BMJV), 2020), and presented in such a way that an accurate view of the company's position is given according to § 289 I and III HGB (BMJV, 2020). Therefore, the keywords in context are analysed. It is assumed that companies, that perceive AI positively, also recognise the impact on financial performance.

Hypothesis H5: Companies, which mention AI-related terms in the context of improvement of products and processes as well as mentioning the concrete financial effect, show a higher financial performance compared to their peers.

Answering the Hypotheses will support the overall research objective to evaluate whether AI-related terms in annual reports are a sufficient explanatory variable to describe financial performance in the German financial service industry.

4. Methodology

4.1. Research Design

Following a deductive research approach, the quantitative content analysis is chosen as an appropriate methodology (White & Marsh, 2006). It is a replicable approach as the content is screened for predefined words, phrases, sentences, or paragraphs (Duriau, Reger, & Pfarrer, 2007). In general, quantitative content analysis is applied to generalise the outcome to a broader population and draw further predictions (White & Marsh, 2006). Compared to interviews and questionnaires, a content analysis shows higher reliability as it is not impacted by the researcher's demand bias (Duriau, Reger, & Pfarrer, 2007). This thesis's objective is to analyse a development over time, which is more challenging to obtain with the use of a survey. However, the limitation is that the approach is less explorative compared to conduct a survey.

An analysis of 25 years of content analyses shows that most papers consider annual reports for the data collection (Duriau, Reger, & Pfarrer, 2007) as annual reports provide insights into the companies' current performance and strategy. Hajek et al. (2014) point out that of the information made available, approx. 20% contain quantitative financial data. Consequently, analysing qualitative information and the impact on financial performance is highly relevant (Hajek, Olej, & Myskova, 2014). Researchers draw a connection between the use of words to related management attention. However, the content of annual reports must be considered critical because the management can use it to influence the external stakeholders. Instead of the top management, public relations specialists might prepare the annual report resulting in a different perspective on the business performance (Duriau, Reger, & Pfarrer, 2007). In the context of AI, one paper applied the content analysis to the annual reports of Malaysian public listed companies. By searching for the words "Artificial Intelligence", "Machine Learning" and "Big Data", the AI awareness and implementation phase has been analysed (Omar, Hasbolah, & Zainudin, 2017).

In this research, keywords and the context of those keywords are analysed. The context includes the 15 words before and after the search term. As the context provides meaning to the individual keyword (Brennan, Guillamon-Saorin, & Pierce, 2009), it gives insight into the AI-business strategy. Moreover, the frequency of AI-related terms for each company from 2016 to 2019 is measured. The resulting variables are incorporated into multiple regressions.

4.2. Data Collection and Validation

4.2.1. Identifying German Domestic Listed Companies in the Finance Sector

Previous researchers of German listed companies chose their dataset based on German stock indexes DAX and MDAX filtered for businesses located in Germany (Dilger & Graschitz, 2015; Gros, Koch, & Wallek, 2017; Schultze, 2005). To increase the sample size, not only companies from the major indexes are considered, instead, all listed companies are included in this research using the database Orbis. When considering the NACE industry classification of Orbis, manufacturing (241), financial and insurance activities (124), and information and communication (90) are the most represented sectors of domestic listed German companies. The dataset is validated by reviewing the publicly quoted status and the NACE industry allocation, resulting in a sample size of 90 financial services companies (Appendix 9.2). Out of the 90 companies, five are excluded as no annual reports are published on their website or by the German federal authorities "Bundesanzeiger". Furthermore, Wirecard is removed due to the known accounting fraud (Storbeck, 2020), resulting in a total of 84 companies being analysed in a timeframe from 2016 to 2019.

4.2.2. AI-related terms in annual reports

The annual reports are retrieved from the company's websites. In some cases, companies are not obliged to publish a management report and only provide financial statements. In this case, the financial statements are solely analysed, and the document type is considered in the analysis.

Some companies were listed after 2016 and therefore did not publish annual reports for the previous years. In four cases, the annual report for 2019 is not published until November 2020. Computer-aided text analysis is applied to ensure a more reliable and faster output (Duriau, Reger, & Pfarrer, 2007). The software Maxqda is used to retrieve the keywords and the corresponding context. Reports, which are not digitalised, are manually reviewed. To ensure a low rater bias, Weber's Protocol is considered while conducting the content analysis. The protocol includes eight steps to establish, test and adopt a coding scheme (Duriau, Reger, & Pfarrer, 2007). To validate the software, a trial round of 20 annual reports is reviewed manually. Based on the sample, it is recognised that the software includes duplicated outputs for 3/20 reports. Therefore, the result is filtered for duplicates to ensure high reliability of the frequency of mentioning terms. The software does not detect words, which are separated, e.g. "big da-ta". Overall, out of the 156 reviewed keywords, Maxqda detected 91% (without considering duplicates it is 97%) correctly. The validation includes the revision of abbreviations to prevent duplicate word counting, and it is checked for words, which are not related to AI. Based on the literature review and the trial around, 33 search keywords are used to analyse 323 annual reports (Table 4). To detect AI-related terms in the context of improvement of product and processes as well as mentioning the concrete financial effect (Hypothesis 3), the frequency of words mentioned in context to AI-terms is analysed. The relevant words are searched for in the previously mentioned context analysis. In the event of uncertainty, the paragraph in the annual report is reviewed.

4.3. Data Analysis

The financial data to define the dependent and the control variable is retrieved from Orbis and Reuters. The corresponding figures were updated on November 14, 2020.

4.3.1. Independent Variables

Through the Content Analysis, nine independent variables are identified. They describe AI-related terms from different perspectives corresponding to the Hypotheses and are used in different models (Appendix 9.4).

4.3.2. Dependent Variables

Different dependent variables are analysed to ensure the robustness of the models. AI Assets will increase in value over time explained by the capability of self-learning. Regarding the market performance, estimating the future value of intangible capital is a challenge (Plastino & Purdy, 2018), as it is assumed that the full value is not captured (Brynjolfsson, Rock, & Syverson, 2017). The advantage of financial market-based variables compared to accounting variables is that they include assumptions of future performances, risks, and account for the value of intangible assets (Brynjolfsson, Hitt, & Kim, 2011). Content analyses of annual reports have assessed financial performance in terms of stock performance (McConnell, Haslem, & Gibson, 1986). Stock returns can directly indicate a change in investors' perception, following public announced company information. Notwithstanding, a causal relationship is difficult to identify as the perception could change because of other firm-specific developments (Bartlett & Partnoy, 2018), next to using AI-related terms in the annual report. Additionally, the full enterprise value is not captured, as stock returns do not include debtholders' return. Instead, it is recommended to directly measure the enterprise value referring to equity's market value and the book value of debt (Bartlett & Partnoy, 2018). In addition, the Price-to-Earnings-ratio (P/E) is considered, which has been applied in previous studies regarding Intellectual Capital (Nassar, 2018). Investors expect higher growth in earnings for companies with a high P/E ratio (Ghaeli, 2016). The ratio could show whether investors expect the same earnings growth potential of AI, as mentioned in the literature.

Regarding accounting performance in the European banking sector, AI significantly impacts ROA. The study is using the share of AI patents as a proxy for AI-implementation. It showed that the variable explains 7% of profitability variations of banks (Kaya, 2019). ROA displays how efficient assets are used to generate income (Maditinos, Chatzoudes, Tsairidis, & Theriou, 2011). Researchers apply different versions of ROAs, while the Net Return on Assets formula is the most frequently used version. The advantage is the simplicity and comparability to other studies. The version considers differences in profitability caused by the debt, and it is respectively controlled for the capital structure. The average total assets are considered as the denominator to match the balance sheet with the income statement and to ensure a more robust variable (Jewell & Mankin, 2011). A study of around 180 US-listed companies showed that data-driven decision-making could be to some extent related to profitability measures, such as ROE and asset utilisation (Brynjolfsson, Hitt, & Kim, 2011). The matching principle is applied by determining the average book value of equity as the denominator (Gallo, 2016). As mentioned previously in the literature review, companies that focus on generating revenue by applying AI are more successful compared to companies aiming to reduce costs. Therefore, revenue growth will be analysed.

4.3.3. Control Variables

The models are controlled for annual report and firm-specific factors. Macro variables such as GDP and interest rate are not considered as the companies are registered in the same country. Although the listed companies are all in the financial service industry, it is controlled for the subindustry. While the average adoption rate is similar across the financial service industry with some outliers in subsectors, the strategic relevance of AI varies between subsectors (Ryll, et al., 2020). Thereupon, the control variable will differentiate between insurance, banks, and other financial services. The document type and the exchange market are included in the analysis to control the annual reports’ different reporting requirements. The document type is considered relevant as some companies did not publish a management report. They only provided financial statements, which might influence the mentioning of AI-related terms. Furthermore, the exchange market is differentiated between regulated and open market. Companies listed on the regulated market must comply with EU requirements. One the other hand, companies listed on the open market are organised under private law with individual terms and conditions depending on the stock exchange (DeutscheBörse, 2020). The different reporting and transparency requirements could impact the mentioning of AI-related terms.

Firm-specific variables such as firm size and risks are integrated into the model. Company size is often applied as a control variable regarding financial performance (Sardo & Serrasqueiro, 2017; Yang, Ying, & Gao, 2020). Anbar & Alper showed that size measured as the natural logarithm of assets has a significant and positive impact on the profitability of banks (2011). Firm risk is measured by the beta factor to identify the systematic risk and by the debt to asset ratio as a measure of unsystematic risk. Both variables are mentioned to negatively impact financial performance in terms of ROA of German listed companies (Velte, 2019). A study of the Turkish Banking Sector found that banks' profitability is negatively impacted by the Long-Term Debt to Total Assets ratio (Ozkan, Cakan, & Kayacan, 2017).

4.3.4. Regression Model

The regression models analyse the impact of mentioning AI-related keywords in the annual reports on financial performance. It is assumed that a time lag exists between adopting AI and realising an impact on financial performance. The literature mentioned that 95% of companies expect an increase in revenue within two years after implementing AI (Ryll, et al., 2020). Considering a two-year lag would reduce the sample size, therefore, the models include one-year lagged independent variables. A missing value analysis is conducted. It is found that for the control variables size and risk, it is preferred to consider assets instead of employees, as well as debt instead of beta. The separate-variance t-test shows that the company's assets significantly influence the missing values for employees and beta. To conduct an ordinary least squares regression, the following assumptions are reviewed with the software SPSS: Outliers, autocorrelation of residuals, multicollinearity, homoscedasticity of residuals, normal distribution of residuals. Outliers are reviewed by considering the cook's distance higher than one (Cook & Weisberg, 1982). The Durbin-Watson test detects autocorrelation of residuals. As the test reviews an error's relationship to the previously shown value, the dataset is organised according to company and years (Brooks, 2014). A variance inflation factor of ten or above implies multicollinearity among the explanatory variables. The histogram and the normal probability plot of the standardised residuals are analysed to review residuals' normal distribution. Lastly, homoscedasticity of residuals is checked by analysing the pattern of the plotted standardised residuals and standardised predicted value (Hair, Black, Babin, & Anderson, 2013).

5. Results

5.1. Data description

The newly created keyword dataset based on the annual reports provides insights into the development of AI-related mentions. German listed financial companies increased AI-related keywords since 2017. Hence Hypothesis **H1a,** which states the increase in AI-related mentions, is supported. Also, the number of companies mentioning AI increased linearly since 2016 (Appendix 9.5). In 2019, 31% of the companies mentioned AI-related keywords in their annual report (in 2016: 11%) (Table 6).

Table 7 provides an overview of the dependent, independent and control variables. From the dataset, 36% of the companies are listed on the regulated market. Moreover, around 10% of the companies only published financial statement reports. Most companies belong to the subindustry other financial services (80%), while 8% can be allocated to insurance and 12% to banks. On average, 45% of banks, 32% of insurances and 16% other financial services mentioned AI-related terms. Regarding financial performance, the mean ROA over the four years is 0.0125% (SD=23.04%). The ROE varies across the companies with a mean of 17.87% (SD=227.24%). For companies, which show negative earnings, the P/E ratio is not reported. The corresponding 217 reports show a mean P/E of 44.45. Overall operating revenue and Enterprise Value grow over the investigated period. The data shows that companies vary considerably in terms of financial ratios.

5.2. Correlations

The Phi/Cramer's V and Contingency Coefficient shown in Table 8 employs a moderately significant relationship between the exchange market and the document type, $r(321)=0.28$, $p<0.01$. In contrast to the regulated market, in the open market some companies release only financial statements report. It is recognised that AI-related keywords are, in general, not mentioned in the financial statement section. Consequently, the regression model will exclude companies, which did not publish a complete annual report. Regarding **H3** "Big Data, Cloud, and AI-related terms are likely to be mentioned in the same annual report", the mentions of Big Data and AI-related terms show a significant moderate relationship $r(321)=0.21$, $p<0.01$. The same applies to AI-related terms and Cloud over the four years analysed, $r(321)=0.20$, $p<0.01$ (Table 9). The Pearson correlation shows no relevant relationship between metric variables (Table 10).

5.3. Regression results

The results obtained could not support the overall Hypothesis, that AI-related terms in annual reports are a sufficient explanatory variable to describe financial performance in the German Financial service industry. However, some evidence is found that AI-related terms positively impact accounting performance. Revenue growth and enterprise value growth are not included in the following models due to the regressions' lack of significance.

The Hypothesis **H1b** “AI-related mentions impact financial performance” is to some extent supported.

$$\text{Fin. performance}_t = ß_0+ß_1\text{AIAdoption}_{t-1}+ß_2\ln(\text{SIZE}_{t-1})+ß_3\text{DEBT}_{t-1} +ß_4\text{DOC}_{t-1}+ß_5\text{MARKET}+ß_6\text{SIND}+ß_7\text{YEAR}+ e \quad (1)$$

$$\text{Fin. performance}_t = ß_0+ß_1\text{AIAdoption}_{t-1}+ß_2\ln(\text{SIZE}_{t-1})+ ß_3\text{DEBT}_{t-1} +ß_4\text{AIAdoptionxSIZE}+ß_5\text{MARKET}+ß_6\text{SIND}+ß_7\text{YEAR}+e \quad (2)$$

Models 1 and 2 have the same inputs with the difference that Model 1 includes financial statements reports. When comparing the two models in Table 11 and Table 12, the impact of the document type is apparent. Besides the previously discussed logic for excluding incomplete annual reports, Model 2 is preferred as the overall significance, and adjusted R^2 is higher.

In Model 2, a size interaction term is tested because the firm size could impact the mentioning of AI-related terms, as in general, larger firms focus more on innovation (Kogan, Papanikolaou, Seru, & Stoffman, 2017). Focusing on AI implementation in multiple processes might result in a financial benefit (McKinsey, 2019). It is found that for ROE, a significant negative size interaction effect exists (Figure 4). In contrast to the initial intuition, smaller companies benefit more from implementing AI than larger companies. One explanation could be that larger firms might have more complex processes, making it more challenging to integrate AI. The AI-adoption coefficient indicates a significant positive impact on ROE, ß=11.13, SE=4.13, $p < 0.01$. For consistency and comparability of the regressions, the interaction term is also included regarding ROA. The AI coefficient is positive, however, not significant, ß=3.14, SE=2.49. Regarding market performance, the P/E variable is transformed by calculating the logarithm of P/E to ensure a normal distribution of residuals. The overall regression is not significant. Nevertheless, R^2 increases when adding the size interaction term (Table 12 and Table 19). According to Hair et al., the significance of the individual coefficients is not relevant, but instead, the incremental R^2 should be evaluated when assessing the interaction term (2013).

The inclusion of the size interaction term results in a significant negative impact of AI adoption on P/E. The AI coefficient is transformed[3] according to the correction for dummy variables in semilogarithmic equations (Halvorsen & Palmquist, 1980). Investors expect a 32.09% lower earnings growth from companies mentioning AI-related terms compared to companies not mentioning it. Due to the existence of autocorrelation, the standard error could be incorrect (Brooks, 2014). Regarding the control variables, size has a significant positive impact on ROE. Although the model cannot explain the variance in financial performance, it indicates that AI-related terms positively impact accounting performance, especially regarding ROE. The following models include size interaction terms, as they describe the AI adoption variable, but from a different perspective and include size as an independent variable.

The Hypothesis **H1c** is tested through Model 3. Instead of considering a dummy variable for AI-related terms, the frequency of AI-related keywords is measured as a ratio. From the data, it is noticeable, that although banks only represent 12% of the data, they mentioned 49% of all AI-related terms. The frequency variable includes the industry impact by relating the company AI-related mentions to the whole industry mentioning.

$$\text{Fin. performance}_t = ß_0 + ß_1 \text{AIFrequency}_{t-1} + ß_2 \ln(\text{SIZE}_{t-1}) + ß_3 \text{DEBT}_{t-1} \qquad (3)$$

$$+ ß_4 \text{AIFrequency} \times \text{SIZE} + ß_5 \text{MARKET} + ß_6 \text{SIND} + ß_7 \text{YEAR} + e$$

Table 13 shows that the frequency of AI-related keywords does not impact financial performance, and therefore H1c is not supported. The AI-frequency variable is less explanatory than the previous AI-variable (Model 2) due to small coefficients with a comparably high standard error. The adjusted R^2 is between 0.5% and 4.4%.

Hypothesis **H2** is testing if companies categorised as early adopters of mentioning AI-related terms show higher performance. Early adopters of AI are defined as companies mentioning AI-related terms since 2016, while late adopters first mentioned it in 2019. From the dataset, 8%

[3] $ß_{transformed} = 100 \times [\exp(ß) - 1]$

can be defined as early adopters and 10% as late adopters. H2 is supported to some extent, suggesting a better performance of early adopters compared to late adopters. Table 14 shows the result of the regressions.

$$\text{Fin. performance}_t = ß_0 + ß_1\text{AILATE} + ß_2\text{AIEARLY} + ß_3\ln(\text{SIZE}_{t-1}) + ß_4\text{DEBT}_{t-1} + ß_5\text{AIEARLY}\times\text{SIZE} + ß_6\text{MARKET} + ß_7 SIND + ß_8\text{YEAR} + e \quad (4)$$

Although not statistically significant, in terms of accounting performance, the coefficient for early adopters is positive (For ROA ß=2.55, SE=4.45, For ROE ß=9.64, SE=7.50). In contrast, the coefficient for late adopters is slightly negative. The company's size has a significant positive impact on ROE, ß=1.43, SE=0.58, $p < 0.05$. Regarding market performance, the model is not significant and shows an R^2 close to zero and is therefore not further analysed.

Hypothesis **H3** expects companies to mention AI-related terms, Cloud and Big Data in the same annual report. In 2019, Big Data (5%), Cloud (18%) and AI-related terms (31%) were mentioned in the annual reports. To understand whether companies state the terms in combination, Model 5 shows a multiple logistic regression.

$$\text{Ln}\left(\frac{p}{1-p}\right) = ß_0 + ß_1\text{CAdoption} + ß_2\text{BDAdoption} + e \quad (5)$$

where p is the probability that AIAdoption = 1

Table 15 and Table 16 indicate that the current model with the inclusion of Cloud and Big Data is more suitable than the null model. However, the model is not a good fit according to the Hosmer-Lemeshow-Test. Thereupon, the H3 is rejected. Furthermore, only 1% of the reports mentioned all three terms in combination. If more companies had mentioned all three terms, it could have been tested whether the combination of technologies would impact financial performance.

Hypothesis **H4** assumes that companies mentioning specific AI-related keywords perform better. Since 2016, the number of specific AI keywords increased from 7% to 20% in 2019. The development also applies to generic keywords, which increased from 7% to 25%.

Table 17 shows that Model 6 cannot explain more than 4.2% in the variation of the dependent variable. In terms of accounting performance, some evidence exists that companies mentioning more specific terms might perform slightly better than companies mentioning generic terms.

$$\text{Fin. performance}_t = ß_0 + ß_1 \text{AIGeneric}_{t-1} + ß_2 \text{AISpecific}_{t-1} + ß_3 \ln(\text{SIZE}_{t-1}) + ß_4 \text{DEBT}_{t-1} + ß_5 \text{AISpecific} \times \text{SIZE} + ß_6 \text{MARKET} + ß_7 \text{SIND} + ß_8 \text{YEAR} + e \qquad (6)$$

For both variables, AIGeneric and AISpecific, an interaction effect with size is tested. The model's explanatory power increased by using the interaction with AISpecific. Regarding accounting performance, the coefficient for specific keywords is positive. However high standard errors exist (For ROA ß=2.78, SE=3.15, For ROE ß=7.51, SE=5.32). In contrast, the coefficient for generic keywords in terms of ROA is slightly negative. Regarding ROE, the AIGeneric coefficient is positive, but smaller, ß=2.13, SE=4.60). Although not statistically significant, it is indicated that a difference between mentioning specific and generic keywords exist. Regarding P/E, the regression is not further considered as the statistical significance is low, and R^2 is close to zero.

Hypothesis **H5** assumes that companies that mention AI in the context of improvement of products and processes as well as mentioning the concrete financial effect show a better performance. Among the companies mentioning AI-related terms, 39% state the above-described context. Figure 3 shows the most frequent words mentioned in connection with AI.

$$\text{Fin. Performance}_t = ß_0 + ß_1 \text{AIAdoption}_{t-1} + ß_2 \text{AIContext}_{t-1} + ß_3 \ln(\text{SIZE}_{t-1}) + ß_4 \text{DEBT}_{t-1} + ß_5 \text{AIAdoption} \times \text{SIZE} + ß_6 \text{MARKET} + ß_7 \text{SIND} + ß_8 \text{YEAR} + e \qquad (7)$$

Table 18 shows the regression results for Model 7. Compared to the previous models, the regression regarding ROE shows the highest R^2 of 7.7%. However, AIContext coefficients are not statistically relevant to support H5. Similar to Model 2, the AI-Adoption variable is significant for ROE, ß=11.87, SE=4.31, $p < 0.01$. The AI-Context coefficient is negative for ROE and ROA and shows a high standard error. The model might indicate that mentioning AI has more impact on financial performance than the mentioned context. The market performance in terms of P/E is not further analysed due to statistical irrelevance. Concluding, none of the model's inputs could explain the variation in financial performance. However, the variable AI-Adoption in Model 2 is showing a significant positive impact on ROE. Although not statistically relevant, AI variables indicate a relatively positive impact on accounting performance.

6. Discussion and limitations

In line with the previously cited analysis of US-listed companies (Perrault, et al., 2019), German listed financial companies increased AI-related keywords in their annual reports. Compared to the US companies, which used the term Machine Learning often, the most mentioned AI-related word by German companies is RPA/Robo-Advisors. The analysis shows that in 2019, 31% of the companies mentioned AI-related words in their annual reports. The result is consistent with the literature that German companies have not yet applied AI widely (PwC, 2020). However, it is worth noting that 45% of banks and 32% of insurance companies mentioned AI-related words compared to only 16% of other financial services.

To the best of the author's knowledge, this research is the first, linking the mentioning of AI-related terms in annual reports to financial performance in terms of ROE, ROA and P/E. In contrast to previous surveys, a robust explanatory relationship is not detected. Still, the AI-Adoption variable has a significant positive impact on ROE. Although not always statistically significant, AI-Adoption, early adopters and specific keywords indicate a positive impact on accounting performance. Regarding market performance, the models lack significance and show an R^2 close to zero. Hence, interpretations of the coefficients are not reliable. One explanation could be that the market has not recognised the benefit of AI-adoption. Investors might find other characteristics of the firm more relevant. It could also be the case that the Price-to-Earnings ratio and Enterprise Value are not suitable variables to detect the benefit, and other variables should be tested going forward.

Although some evidence is provided for the Hypotheses that AI adoption has a positive effect on accounting performance, the models miss explanatory power and variables lack significance. Four possible interpretations can explain the results. Firstly, the small numbers of firms and narrowing the AI-Adoption variable could describe the lack of explanatory power. Secondly, annual reports do not provide enough insights into AI-implementation. Companies that mentioned AI-related terms have not adopted AI yet or only adopted AI in one business unit.

Moreover, not all companies implementing AI have mentioned AI-related terms. Another interpretation is that only mentioning AI-related terms is not enough to achieve financial impact. As mentioned in the literature review, the benefit of adopting AI cannot be expected automatically (Ransbotham S. , Khodabandeh, Fehling, LaFountain, & Kiron, 2019). Moderators, such as data-driven company culture, data quality, top management leadership, and talent management are also needed to drive success. Lastly, it might be the case that other events, such as organisational change and market development, have a more substantial impact on overall business performance. The benefit of AI-implementation could be instead noticed on the business unit level or process level.

Several limitations of the study should be mentioned, as well as the corresponding future research opportunities. The dataset compromises four years and one year is considered for the AI-impact to realise. The time frame is relatively short, especially as the trend of AI is still developing. Through a longitudinal study, researchers might find support for the Hypothesis, also considering a more extended period for the realisation of AI-benefits. This research only analysed listed companies in the financial service industry in Germany. Hence, only 84 companies are reviewed. The implications and the AI-adoption rate could be different for other industries and private companies in various countries. Future research could investigate other sectors and consider other published information by the company and publications of third parties. Companies developing AI-applications often mention use cases and point out the benefit in hours and expenses saved. Additionally, the reliability of mentioning AI-related terms in annual reports could be tested by interviewing the respective company. In this research, the OLS assumptions are mostly tested based on graphs, and it is not reviewed for linearity. Moreover, it is not considered that in the presence of lagged variables, the Durbin-Watson test would be biased. Therefore, autocorrelation is not always detected (Brooks, 2014). Future research could test for the OLS assumption more extensively considering, e.g. White-Test, Kolmogorov-Smirnov-Test. The research design is not considering the extent to which AI-Adoption is implemented and which other variables moderate AI-adoption success. More complex models could include moderators such as data-driven company culture and test for other financial performance metrics.

7. Conclusion

This research conducts a new approach by measuring AI-adoption through a quantitative research design and linking the newly created variables to financial performance. Previous studies measured the AI-Adoption through surveys and found a positive impact on performance. This thesis tests whether AI-related references in annual reports could be used as an explanatory variable for financial performance in terms of ROA, ROE and P/E. The models could not explain the variation in financial performance based on AI-related mentions but indicate a positive impact on accounting performance. The annual report's analysis shows a linear increase in the frequency of AI-related terms since 2017 and an increase in companies mentioning AI since 2016. This development indicates that financial service companies are more aware of AI, yet they are still at an early AI-implementation stage. As the trend of AI-adoption is still developing, and the financial benefit takes time to realise, plenty of research opportunities exist contributing to a deeper understanding of business implications.

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9. Appendix

9.1. Literature Review of Artificial Intelligence

Table 1: Categories of AI techniques and functional applications (WIPO, 2019)

AI techniques	**AI functional applications**
Machine learning	Speech processing
Probabilistic reasoning	Predictive analysis
Ontology engineering	Distributed AI
Logic programming	Natural language progressing
Fuzzy logic	Robotics
	Planning and scheduling
	Computer vision
	Control methods
	Knowledge representation and reasoning

Table 2: Application of AI in the Financial Sector (van der Burgt, 2019*;* Zetzsche, Arner, Buckley, & Tang, 2020)

Areas of AI applications	**Example of processes and functions**
Customer Services	On-boarding process (e.g. identity verification) Targeted Marketing Relationship Management (e.g. Spending metrics, Speech recognition in customer support)
Operations and Risk	Loan Application (e.g. Stress Tests and Credit Rating) Automated Analysis of Documents (e.g. Credit agreements) Insurance claims processing
Trading and Portfolio Management	Capital Allocation Robotic Advisors Algorithmic trading Bond Pricing
Regulatory compliance and supervision	Transaction Data Analysis Fraud Detection (e.g. Anti-money laundering monitoring, Identity theft)
Payments and Infrastructure	Intelligent Chatbots
Data security and monetisation	Cybersecurity solutions

9.2. Data Validation of German domestic listed companies in the Financial Industry

The Orbis database includes companies, which are still active and still liquid as of 29.06.2020 and consist of 124 financial services businesses. To validate the sample size, the public quoted status and the NACE industry classification are reviewed. The listed status is evaluated based on a comparison to all German stock exchanges and the Reuters dataset. In the case the company was not found via the additional sources, the company is not further included in the database. The industry allocation is compared to the company NACE code published by the German Federal Bank in March 2020, which includes German public limited companies with a share capital of or above EUR 2.5 million. As the German Federal Bank is an official institution, it is assumed that the information shows high reliability. If a company is not included in the Bundesbank data, the stock exchange industry allocation is defined as the leading indicator. The allocated sectors of the stock exchanges are mainly comparable with the SIC, respectively NACE industry classification (Dilger & Graschitz, 2015). Besides, companies assigned to the financial sector according to German stock exchanges and Reuters are cross reviewed, and in the case of industry confirmation, they are added to the database.

Table 3: Validation of sample size

Validation	**Nr. of companies**
Orbis original dataset	**124**
Companies delisted	-10
Companies with a different NACE code (Bundesbank)	-33
Companies with a different industry allocation (stock exchange)	-10
Companies in the Financial Industry	19
Companies analysed	**90**

9.3. Search Keywords in annual reports

Table 4: Search keywords used in the Content Analysis

AI-related Search keywords	Other Search keywords
Advanced analytics, Artificial, Artificial Intelligence, AI, chatbo*, Computerlinguistik, Computer Vision, Deep Learning, Künstlich* Intelligenz, künstlich*, KI, linguistischen Datenverarbeitung, Machinelles Lernen, Machine Learning, machinell* lernverfahren, maschinellem Lernen, Neurona* Netzwer*,Neural Networ*, Natural language, Robotik, Roboti*, Roboter, Robotergesteuerte Prozessautomatisierung, Robo-Advisor, RPA, virtuell* Agent*	Big-Data, Big Data, Börse 4.0, Cloud, Data analytics, Industrie 4.0

Note: Lower and upper case of the keywords are included in analysis, *different word ending possibilities.

9.4. Variables

Table 5: Independent, dependent and control variables

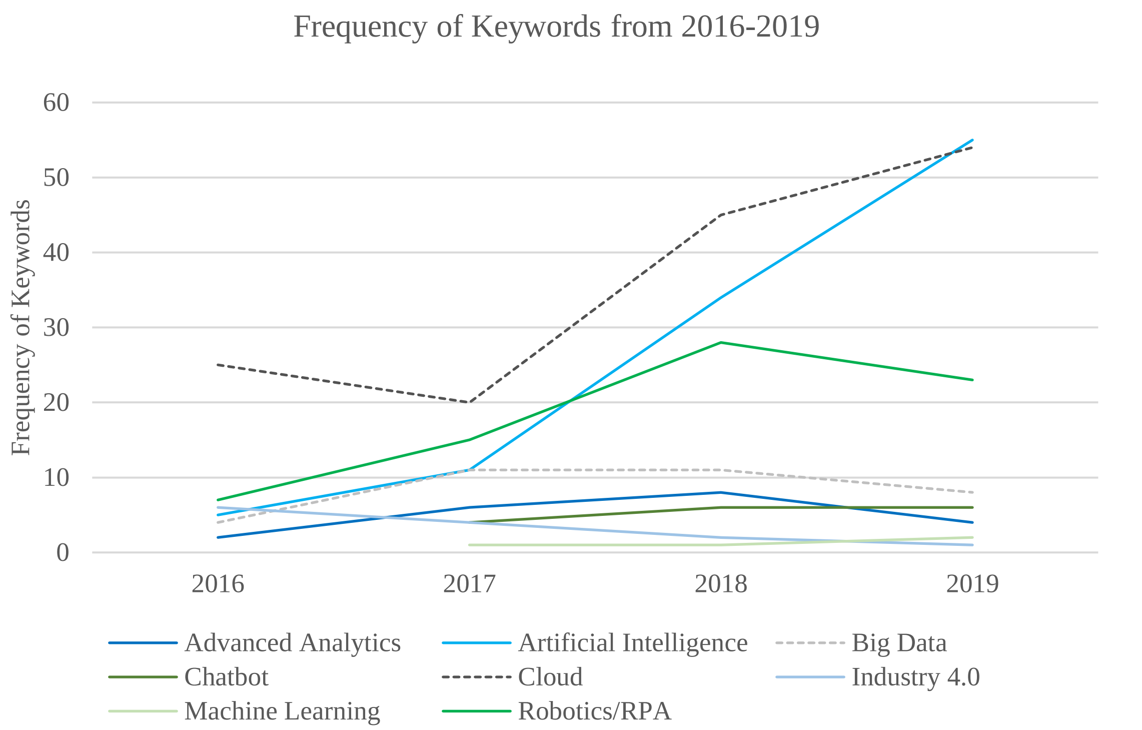
Variable	Code	Variable measurement	Literature
1. Independent Variables			
Artificial-related terms	AIAdoption	AI-related term mentions if yes=1; no= 0 The variable includes the subcategories of the concept of Artificial Intelligence.	n/a
	AIFrequency	The variable is calculated as a ratio=company number of words/ Total Industry words	n/a
	AIEarly	Early Adopters of AI if mentioned since 2016 and still stated AI-related terms in 2017 and 2018=1; others=0	n/a
	AILate	Late Adopters of AI if first mentioned AI-related terms in 2019=1; others=0	n/a
	AIContext	AI referred to as an improvement in processes and products if yes= 1; no=0	n/a
	AIGeneric	Generic Keywords of AI (Industry 4.0, Advanced Analytics, Artificial Intelligence) if yes=1; others= 0	n/a
	AISpecific	Specific Keywords of AI (Machine Learning, Robotics/RPA/Robo-Advisor, Chatbot) if yes=1; others= 0	n/a
	Interaction-term (SIZE)	Interaction term(SIZE)= $\text{SIZEA}_{\text{meancentered}} \times \text{AIVariable}_{\text{meancentered}}$	n/a
	BDAdoption	Big data mentions if yes=1; no= 0 Big Data is not considered as an Artificial related term.	n/a
	CAdoption	Cloud mentions if yes=1; no= 0 Cloud is not considered as an Artificial related term.	n/a

Table 5: Independent, dependent and control variables (continued)

Variable	Code	Variable measurement	Literature
2. Dependent Variables			
Market Performance	EVG	Growth in Enterprise Value $= \frac{E_{Market(t)}+D_{Book(t)}-E_{Market(t-x)}+D_{Book(t-x)}}{E_{Market(t-x)}+D_{Book(t-x)}}$	(Lee, Kwon, & Pati, 2019)
	P/E	$P/E = \frac{\text{Market Capitalisation}}{\text{Net Income}}$ P/E is shown as a logarithm to ensure a normal distribution of residuals in the regression.	(Nassar, 2018)
Accounting Performance	ROA	$\text{Return on Assets(ROA)} = \frac{\text{Net Income}}{\text{Average Total Assets}}$	(Kaya, 2019), (Soana, 2011), (Brynjolfsson et al., 2011), (Maditinos et al., 2011), (Lee et al., 2019) (Yang et al., 2020)
	ROE	$\text{Return on Equity(ROE)} = \frac{\text{Net Income}}{\text{Average Total Equity}}$	(Soana, 2011), (Brynjolfsson et al., 2011), (Maditinos et al., 2011)
	REVG	$\text{Revenue growth} = \frac{\text{Revenue}_t - \text{Revenue}_{t-x}}{\text{Revenue}_{t-x}}$	(Maditinos et al., 2011)
3. Control Variables			
Document	DOC	Annual report (Management report and the financial statements) =1; only the financial statement report= 0	n/a
Exchange market	MARKET	Regulated market =1; Open market = 0	n/a
Subindustry	SIND	Categorical measure = Bank, Insurance and Other Financial Services	n/a
Firm Size	SIZEA SIZEE	Total Asset =log (total Assets) Employees =log (number of employees)	(Kogan et al., 2017) (Yang et al., 2020) (Sardo & Serrasqueiro, 2017) (Anbar & Alper, 2011)
Firm risk	DEBT BETA	Debt= Total Debt/Total Assets BETA measures the movement in the stock price with the movements in the market.	(Maditinos et al., 2011), (Sardo & Serrasqueiro, 2017), (Ozkan et al. 2017), (Velte, 2019)

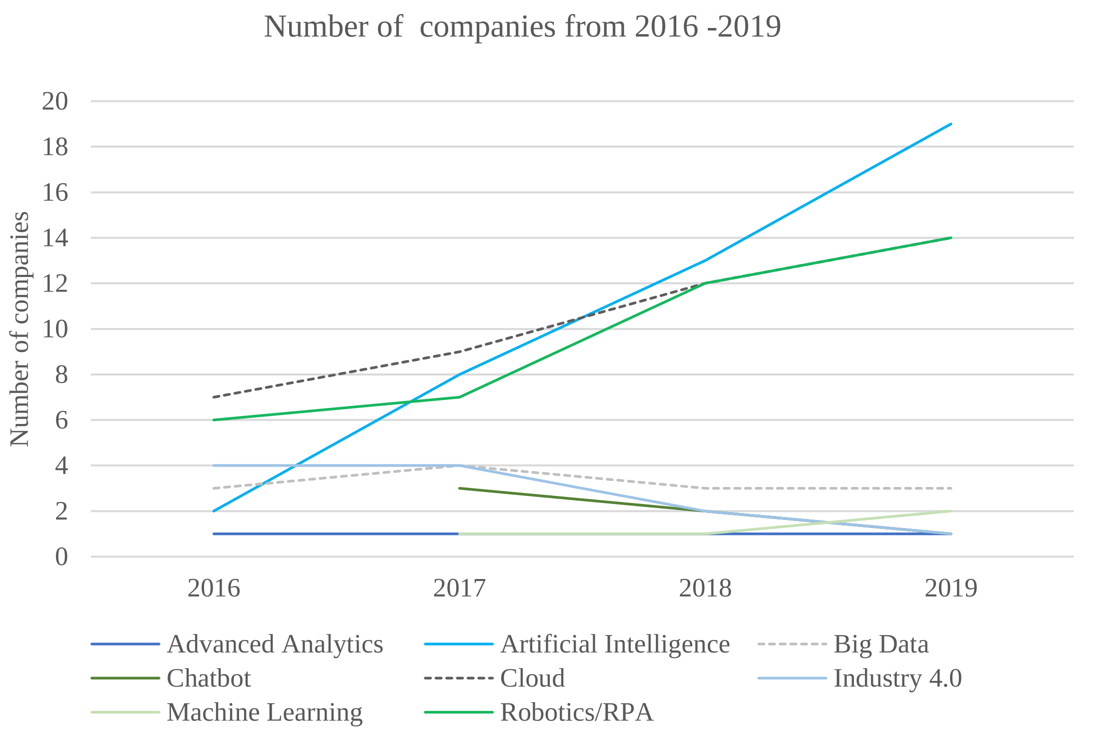
9.5. Data exploration annual reports of German listed Financial companies

Figure 1: Frequency of keywords in annual reports from 2016-2019



Note: For comparability graphs are adjusted for companies, which did not publish an annual report in all four years (N=75 companies). Dotted lines are not related to Artificial Intelligence.

Figure 2: Number of companies mentioning keywords from 2016-2019



Note: For comparability graphs are adjusted for companies, which did not publish an annual report in all four years (N=75 companies). Dotted lines are not related to Artificial Intelligence.

Figure 3: Word cloud showing the most frequent words in context to AI-related terms (H5)

Note: The Context is defined as 15 words before and after the appearance of AI-related mentions.

9.6. Descriptive Statistics

Table 6: SPSS Output Descriptive Statistics for AI-related terms from 2016-2019

Descriptive Statistics individual years

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
AIAdoption 2019	80	0	1	.31	.466	.218
AIAdoption 2018	85	0	1	.24	.427	.182
AIAdoption 2017	80	0	1	.19	.393	.154
AIAdoption 2016	81	0	1	.11	.316	.100

Table 7: SPSS Output descriptive Statistics from 2016-2019

Descriptive Statistics of four years combined

	N	Minimum	Maximum	Mean	Std. Deviation
MARKET	252	0	1	.36	.480
SIND Insurance	252	0	1	.08	.277
SIND Bank	252	0	1	.12	.324
DOC	243	0	1	.88	.320
SIZEA	240	4.17	21.11	11.82	3.846
DEBT	240	0.00%	87.18%	13.649%	22.595%
ROA	236	-171.68%	186.49%	0.013%	23.044%
ROE	232	-438.70%	3362.86%	17.871%	227.239%
P/E	217	.02	1098.46	44.449	117.332
Natural Log of P/E	217	-4.18	7.00	2.843	1.187
REVG	226	-197.47%	2562.50%	54.733%	272.633%
EVG	222	-84.01%	17153.29%	103.274%	1162.111%
AIAdoption	243	0	1	.24	.427
AIContext	59	0	1	.39	.492
AIFrequency	243	0	24	1.01	2.902
AIEarly	237	0	1	.08	.265
AILate	243	0	1	.10	.299
CAdoption	243	0	1	.15	.356
BDAdoption	243	0	1	.05	.217
AISpecific	243	0	1	.16	.372
AIGeneric	243	0	1	.19	.396

9.7. Correlations

Table 8: SPSS Output Phi/Cramer's V and Contingency Coefficient for nominal variables (DOC, AIAdoption, MARKET)

Symmetric Measures		**AIAdoption/DOC**		**DOC/MARKET**	
		Value	Approx. Sig.	Value	Approx. Sig.
Nominal by Nominal	Phi	.190	.001	.277	.000
	Cramer's V	.190	.001	.277	.000
	Contingency Coefficient	.186	.001	.267	.000
N of Valid Cases		323		323	

Table 9: SPSS Output Phi/Cramer's V and Contingency Coefficient for nominal variables (AIAdoption, BDAdoption, CAdoption)

Symmetric Measures		**AIAdoption/ BDAdoption**		**AIAdoption/ CAAdoption**	
		Value	Approx. Sig.	Value	Approx. Sig.
Nominal by Nominal	Phi	.214	.000	.204	.000
	Cramer's V	.214	.000	.204	.000
	Contingency Coefficient	.209	.000	.200	.000
N of Valid Cases		323		323	

Table 10: SPSS Output Pearson Correlations

Pearson Correlations (Metric Variables)

		ROANI	P/E	ROENI	REVG	EVG	SIZEE	SIZEA	BETA	DEBT	AIFreq.
ROANI	Pearson Correlation	1	-,348**	.610**	.022	.118	.107	.130*	-.156*	.000	.021
	Sig. (2-tailed)		,000	.000	.748	.080	.092	.022	.011	.997	.714
	N	311	148	306	215	222	249	311	266	311	304
P/E	Pearson Correlation	-,348**	1	-,477**	-,048	,064	-,177*	-,126	-,058	,105	-,050
	Sig. (2-tailed)	,000		,000	,562	,441	,046	,128	,495	,204	,547
	N	148	148	148	146	145	127	148	139	148	147
ROENI	Pearson Correlation	.610**	-,477**	1	-.010	.070	-.025	.002	-.187**	-.025	-.009
	Sig. (2-tailed)	.000	,000		.890	.302	.697	.975	.002	.668	.870
	N	306	148	306	213	219	246	306	262	306	300
REVG	Pearson Correlation	.022	-,048	-.010	1	.255**	-.146*	-.183**	-.116	.025	-.056
	Sig. (2-tailed)	.748	,562	.890		.000	.044	.007	.102	.710	.404
	N	215	146	213	226	210	190	217	200	217	225
EVG	Pearson Correlation	.118	,064	.070	.255**	1	-.066	-.026	-.042	-.024	-.026
	Sig. (2-tailed)	.080	,441	.302	.000		.374	.699	.551	.726	.702
	N	222	145	219	210	222	182	222	205	222	218
SIZEE	Pearson Correlation	.107	-,177*	-.025	-.146*	-.066	1	.888**	.401**	.071	.302**
	Sig. (2-tailed)	.092	,046	.697	.044	.374		.000	.000	.262	.000
	N	249	127	246	190	182	260	251	224	251	257
SIZEA	Pearson Correlation	.130*	-,126	.002	-.183**	-.026	.888**	1	.288**	.134*	.305**
	Sig. (2-tailed)	.022	,128	.975	.007	.699	.000		.000	.017	.000
	N	311	148	306	217	222	251	316	266	316	306
BETA	Pearson Correlation	-.156*	-,058	-.187**	-.116	-.042	.401**	.288**	1	.175**	.170**
	Sig. (2-tailed)	.011	,495	.002	.102	.551	.000	.000		.004	.006
	N	266	139	262	200	205	224	266	267	266	263
DEBT	Pearson Correlation	.000	,105	-.025	.025	-.024	.071	.134*	.175**	1	-.055
	Sig. (2-tailed)	.997	,204	.668	.710	.726	.262	.017	.004		.334
	N	311	148	306	217	222	251	316	266	316	306
AIFreq.	Pearson Correlation	.021	-,050	-.009	-.056	-.026	.302**	.305**	.170**	-.055	1
	Sig. (2-tailed)	.714	,547	.870	.404	.702	.000	.000	.006	.334	
	N	304	147	300	225	218	257	306	263	306	323

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

9.8. Regression Models

Table 11: Regression summary for Hypothesis 1b Model 1

Model 1 - Hypothesis 1b: Mentioning AI-related terms			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIAdoption	-.095	-27.623	-.146
	(4.091)	(44.177)	(.258)
SIZEAssets	1.332**	15.586**	-.045
	(.585)	(6.448)	(.045)
DEBT	-.035	-.645	.008*
	(.069)	(.751)	(.004)
MARKET	-4.469	-29.271	-.153
	(3.523)	(38.069)	(.263)
DOC	7.228	-160.588***	-.528
	(4.807)	(54.881)	(.379)
CONSTANT	-12.520*	6.731	3.851***
	(6.467)	(70.955)	(.507)
Observations	228	225	162
Adjusted. R^2	.046	.022	.027
F	2.220	1.571	1.503
Sig. Model	.022	.125	.152
Durbin-Watson	1.938	1.954	1.805
Dummies Industry/Year	YES	YES	YES
Limitation	n/a	Outliers, Non normal distribution	n/a

Notes: All models include fixed effects for the Year and the Subindustry. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

Table 12: Regression summary for Hypothesis 1b Model 2

Model 2 - Hypothesis 1b: Mentioning AI-related term			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIAdoption	3.142	11.129***	-.387*
	(2.490)	(4.132)	(.233)
AIAdoption x Size	-.471	-2.714***	.089
	(.588)	(.976)	(.055)
SIZEAssets	0.249	1.344**	.010
	(.341)	(.566)	(.038)
DEBT	-0.23	-.021	.006
	(.041)	(.068)	(.004)
MARKET	-1.869	-3.568	-.346
	(2.011)	(3.336)	(.217)
CONSTANT	4.964	-3.139	2.810***
	(3.754)	(6.228)	(.412)
Observations	202	202	148
Adjusted. R^2	.051	.080	.016
F	2,193	2.941	1.258
Sig. Model	.024	.003	.265
Durbin-Watson	2.033	1.837	1.534
Dummies Subindustry/Year	YES	YES	YES
Limitation	n/a	n/a	Auto-Correlation

Notes: All models include fixed effects for the Year and the Subindustry. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

Figure 4: Interaction effect between AI-Adoption and Size in terms of Assets

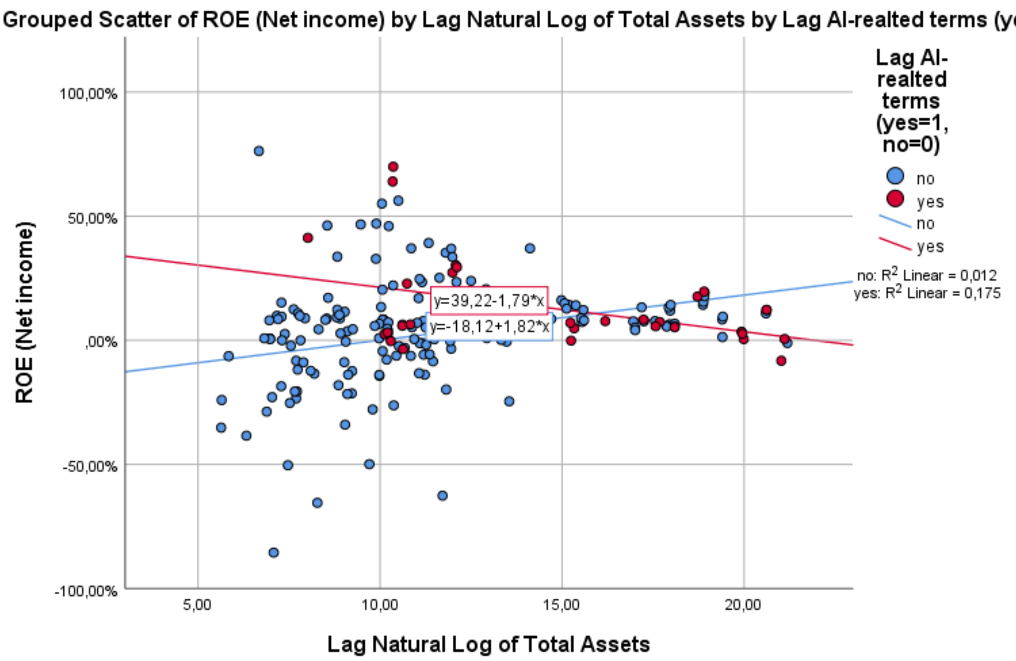


Table 13: Regression summary for Hypothesis 1c Model 3

Model 3 - Hypothesis 1c: AI-Frequency			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIFrequency	.123	.466	-.038
	(.373)	(.633)	(.035)
AIFrequency x Size	-.007	-.100	.005
	(.071)	(.120)	(.007)
SIZEAssets	.032	1.020**	-.001
	(.270)	(.459)	(.029)
DEBT	-.004	.022	.006
	(.039)	(.066)	(.004)
MARKET	-2.197	-4.996	-.311
	(1.943)	(3.302)	(.212)
CONSTANT	6.939**	-.055	2.866***
	(3.372)	(5.730)	(.359)
Observations	202	202	148
Adjusted. R²	.044	.028	.005
F	2.310	1.826	1.105
Sig. Model	.028	.084	.363
Durbin-Watson	1.989	1.757	1.552
Dummies Year	YES	YES	YES
Limitation	n/a	n/a	Auto-Correlation

Notes: All models include fixed effects for the year. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

Table 14: Regression summary for Hypothesis 2 Model 4

Model 4 - Hypothesis 2: Timing of AI-mentions			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIEarly	2.553	9.635	-.342
	(4.445)	(7.498)	(.397)
AILate	-.008	-1.997	.168
	(2.764)	(4.662)	(.292)
AIEarly x Size	-.497	-2.916	.102
	(1.191)	(2.009)	(.104)
SIZEAssets	.300	1.426**	.012
	(.344)	(.580)	(.038)
DEBT	-.024	-.022	.006
	(.043)	(.072)	(.004)
MARKET	-2.144	-4.579	-.335
	(2.059)	(3.473)	(.225)
CONSTANT	4.683	-2.854	2.739***
	(3.854)	(6.501)	(.418)
Observations	200	200	147
Adjusted. R^2	.039	.036	-.009
F	1.800	1.750	.872
Sig. Model	.063	.072	.561
Durbin-Watson	2.044	1.823	1.558
Dummies Subindustry/Year	YES	YES	YES
Limitation	n/a	n/a	Auto-Correlation

Notes: All models include fixed effects for the Year and the Subindustry. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

Table 15: SPSS Output Multiple Logistic Regression Model 5- Categorical Variables

Categorical Variables Codings			
			Parameter coding
		Frequency	(1)
CAAdoption	No	280	1.000
	Yes	43	.000
BDAdoption	No	308	1.000
	Yes	15	.000

Table 16: SPSS Output Multiple Logistic Regression Model 5- Hosmer and Lemeshow Test

Hosmer and Lemeshow Test			
Step	Chi-square	Df	Sig.
1	.000	0	.

Table 17: Regression summary for Hypothesis 4 Model 6

Model 6 - Hypothesis 4: Specific and Generic keywords			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIGeneric	-1.023	2.126	-.103
	(2.726)	(4.599)	(.268)
AISpecific	2.776	7.510	-.350
	(3.153)	(5.320)	(.290)
AISpecific x Size	-.210	-2.086*	.057
	(.745)	(1.257)	(.071)
SIZEAssets	.325	1.444**	.017
	(.356)	(.601)	(.039)
DEBT	-.025	-.013	.005
	(.041)	(.070)	(.004)
MARKET	-1.950	-4.779	-.315
	(2.032)	(3.428)	(.221)
CONSTANT	4.335	-3.959	2.730***
	(3.893)	(6.566)	(.430)
Observations	202	202	148
Adjusted. R^2	.042	.040	-.006
F	1.878	1.839	.912
Sig. Model	.050	.056	.524
Durbin-Watson	2.038	1.813	1.533
Dummies Subindustry/Year	YES	YES	YES
Limitation	n/a	n/a	Auto-Correlation

Notes: All models include fixed effects for the Year and the Subindustry. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

Table 18: Regression summary for Hypothesis 5 Model 7

Model 7 - Hypothesis 5: AI in the context of improvement			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIAdoption	3.178	11.865***	-.382
	(2.600)	(4.309)	(.239)
AIContext	-.246	-5.116	-.045
	(5.034)	(8.345)	(.486)
AIAdoption x Size	-.455	-2.379**	.092
	(.676)	(1.120)	(.065)
SIZEAssets	.253	1.416**	.011
	(.349)	(.579)	(.039)
DEBT	-.024	-.026	.006
	(.041)	(.068)	(.004)
MARKET	-1.868	-3.549	-.346
	(2.016)	(3.342)	(.218)
CONSTANT	4.917	-4.072	2.801***
	(3.874)	(6.421)	(.425)
Observations	202	202	148
Adjusted. R^2	.046	.077	.008
F	1.964	2.676	1.125
Sig. Model	.039	.004	.348
Durbin-Watson	2.033	1.846	1.534
Dummies Subindustry/Year	YES	YES	YES
Limitation	n/a	n/a	Auto-correlation

Notes: All models include fixed effects for the Year and the Subindustry. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

Table 19: Regression summary for Hypothesis 1b Model 2 without Interaction terms

Model 2 - Hypothesis 1b: Mentioning AI-related terms without Interaction terms			
Regressions Variables	**(1) ROA**	**(2) ROE**	**(3) P/E**
AIAdoption	2.329	6.444*	-.221
	(2.271)	(3.837)	(.210)
SIZEAssets	.250	1.349**	.014
	(.341)	(.576)	(.038)
DEBT	-.019	.003	.005
	(.040)	(.068)	(.004)
MARKET	-2.207	-5.512	-.293
	(1.964)	(3.318)	(.215)
CONSTANT	5.012	-2.850	2.745***
	(3.750)	(6.335)	(.412)
Observations	202	202	148
Adjusted. R^2	.052	.048	.004
F	2.392	2.264	1.082
Sig. Model	.018	.025	.379
Durbin-Watson	2.032	1.792	1.537
Dummies Subindustry/Year	YES	YES	YES
Limitation	n/a	n/a	Auto-correlation

Notes: All models include fixed effects for the Year and the Subindustry. The variables are described by the unstandardised coefficients B. The std. errors are shown in parenthesis. The significance is indicated at the 1% (***),5% (**) and 10% (*) levels.

9.9. List of Abbreviations

Abbreviation	**Explanation**
ROA	Return on Assets
ROE	Return on Equity
P/E	Price-to-Earnings Ratio
AI	Artificial Intelligence
ML	Machine Learning
RPA	Robotic Process Automation
OLS	Ordinary Least Square
SE	Standard Error
SIND	Subindustry
NACE	Nomenclature of Economic Activities
SIC	Standard Industrial Classification
BaFin	German Federal Financial Supervisory Authority
Approx.	Approximately