FINANCIAL REPORTING IN THE ERA OF AI: THE RESPONSE OF COMPANIES IN THE NETHERLANDS TO THE CHALLENGES POSED BY MACHINE READERSHIP

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Abstract

This thesis investigates the impact of Artificial Intelligence (AI) on financial reporting practices in medium to large, listed companies in the Netherlands. By surveying financial managers, accountants, and related professionals, the study explores how AI tools are influencing financial disclosures, the challenges this entails for companies and the strategies companies adopt in response. The findings highlight a dual effect of AI integration on the side of the financial markets: while AI enhances the efficiency and precision of financial analysis, it also introduces significant risks. The overreliance on AI-generated outputs can lead to biases and a reduction in human oversight, complicating investment decisions and market operations.

In response, companies are planning on implementing several strategic measures, such as meticulous drafting of financial statements, compliance with existing regulations, enhanced employee training with AI tools, fostering open communication with both employees and investors, and conducting internal audits to mitigate risks. These adaptations underscore the necessity of balancing AI's advantages with continuous human involvement to get the best out of this intelligent tool.

The paper also addresses broader implications, including ethical concerns about fairness and transparency, the need for updated legal standards for AI use in finance, and the societal impact it could have on employment and skills. Therefore, it calls for interdisciplinary collaboration to maximise AI benefits, while aligning its use with important societal values.

To sum up, this study provides valuable insights into the challenges and opportunities of AI in financial reporting, emphasising the need for a balanced approach to ensure an ethical and effective integration of AI in the financial sector. That way, all sorts of stakeholders can benefit from this invention and increase social welfare together. And despite the importance of this paper and its findings, it still has its limitations and as AI continues to evolve and become more common in the future, there will certainly be more room for other research projects into this novel topic.

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1. Introduction

Only a couple of years ago, innovations such as artificial intelligence and machine learning were something from the realm of imagination and science fiction. They seemed as likely to enter our lives as flying cars or robotic pets, until the 80's and 90's, when breakthroughs in surpassing human intellectual ability were made in fields like chess (Hsu, 2002) and when 'expert' systems, like AI, became a standard part of the industrial repertoire for checking circuit boards and detecting credit card fraud (Liao, 2005). From there on, the functions of AI have only expanded. They went from fraud detection to searching through massive amounts of data to find the information required by a human user and further, to reading emotions and detecting lies (Schuller et al., 2016). However, as helpful as artificial intelligence is in various domains, the power it has presents great societal dangers. AI can forge signatures, imitate someone's handwriting, and alter live videos (Hancock et al., 2007; Thies et al., 2016). It also has the ability to influence the outcomes of elections and help cyber criminals extract the personal data of almost anyone in the world (Russell & Norvig, 2021; Bostrom, 2014). This powerful and life-altering innovation has reached almost all aspects of life and will keep expanding in the near future.

For that reason, and due to the significant impact AI has had on the following section of the economy, this study will focus on the financial sector and the effect that algorithms have had on it. This big and influential sector has been deeply transformed by AI, particularly given the historically high risk of fraudulent activity and the need to constantly manage new risks (see fig. 1). It has made it more efficient, secure, innovative, open, and developed than ever before. For instance, algorithms can now analyse customer data to develop a deeper understanding of their needs and enable financial institutions to design personalized experiences that meet them (Fernandez, 2019; Yalamati, 2023).

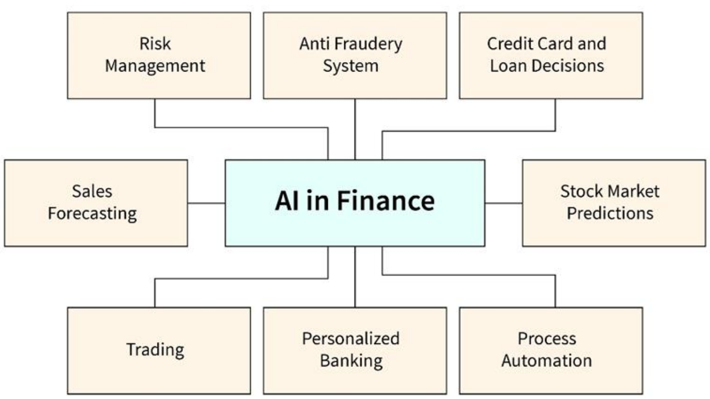

Figure 1: The many roles and uses of AI in the financial sector

Despite these positive changes, the financial sector has also become very dependent on technology, which can give erroneous outputs, leading to significant financial losses or incorrect credit decisions, that may unfairly affect individuals and businesses. It has also become more indifferent and impersonal, meaning that it went astray from the initial values, that the people founding the first institutions in this sector had (Hosen et al., 2023). The switch from community focus and stability to global reach and profit focus has changed the relationship between financial institutions and other actors in the economy forever. Thus, examining the positive and negative effects of AI on this area is especially interesting, even more so from the perspective of companies operating within it, as they are key market participants impacted by algorithms and their side of the story is least understood at the moment.

To study this emerging phenomenon effectively, this research specifically targets the financial reporting activities of the above-mentioned companies and the related complexities arising from AI's introduction in their close environment, so on the side of the financial markets. That is because investors use algorithms specifically for reading those financial reports (i.e., annual and quarterly reports, conference calls, financial statements, etc.), to make forecasts and predictions, as well as estimate risks and make actual investment decisions (Mirza & Anwar, 2023). So, it is much easier to understand how companies are affected by this change, based on how they react to it and the strategies that they choose to deploy.

It is already known from previous research that AI-generated predictions tend to be biased and difficult to interpret, which is helpful in forming an idea about what companies are dealing with (Doshi-Velez & Kim, 2017). However, algorithms and the way that they are built (i.e., their black-box nature) are not the whole issue here. It is the way they are used that is even more alarming. So, it is the current overreliance of investors on these outputs that is damaging for companies in many ways (e.g., they could have difficulties raising capital when they would need it the most) (O'Neil, 2016; Yalamati, 2023).

On that account, understanding how companies react to this, namely the way in which they adjust their financial reporting to the continuously increasing AI readership from investors and analysts, is relevant for many stakeholders and should be studied more. For example, a deeper comprehension of this occurrence would enable investors and investment groups to better interpret and analyse financial information, leading to more timely and informed investment decisions. It would also help regulators oversee the relationship between companies and investors in a better way, making sure that investors use AI in an appropriate and ethical manner, and that companies do not misreport financial information out of fear of it being misunderstood by a machine, which takes information out of context (Koch, 2024). This would consequently make financial markets more efficient, flourishing, transparent, safe, and trustworthy, which would result in an increase in welfare all over the world.

Therefore, the research question of this paper is as follows: "*What impact does the growing integration of AI tools in the financial sector have on the characteristics of companies' financial reporting? Furthermore, what are the emerging challenges and considerations that companies are faced with as they navigate this evolving landscape?*" The "impact" this question refers to is the effect that these tools have on the financial reporting of companies, and the "challenges" are the obstacles that companies are currently facing. So, companies' financial reporting could, for example, become more structured and detailed (these are possible impacts), but also meticulously written, time-consuming, and positively biased (these are possible and expected challenges), as a result of this AI integration on the side of the financial markets. They would likely start using NLP techniques to enhance the readability and interpretability of textual information in financial reports and semantic tagging to provide additional context and meaning to machine readers (these are possible considerations, so things that companies would take into account when making their financial reports) (Meurers, 2012). However, there is no way of knowing for sure until we ask companies themselves.

Considering that, this paper hopes to find an answer to the above-addressed research question by carefully studying the existing base of academic literature on the topic (see the following section) and creating a novel, tailored survey, based on the hypotheses derived from the findings in the literature review below, that will help in gathering insightful data from the source itself, the financial workers (financial managers, accountants, etc.) of listed companies in the Netherlands.

2. Literature review

In recent years, the integration of artificial intelligence (AI) tools within the financial sector has emerged as a focal point of scholarly investigation, instigating discussions regarding its profound implications for financial reporting decisions. This literature review attempts to shape a refined perspective on the topic by delving into the evolving landscape of AI adoption in finance, synthesizing key insights from seminal works and meticulously addressing identified research gaps. Through a comprehensive analysis of key scholarly contributions this review aims to provide a deeper understanding of the intricate interplay between AI and financial reporting.

2.1 Theoretical concept and research gap

This section will commence by contouring the logical base of this research. Over the next few pages, we are going to delve into the way in which financial analysts and portfolio/asset managers use AI to analyse the financial information of companies (reports, conference calls, etc.) and give investment advice to hedge funds and other investor groups (see fig. 2). Without grasping this part of the topic (the right side of our graph), it is difficult to learn how these actions from the side of the investors and analysts affect companies, and how they respond to that (the left side of the graph). It is important to mention, however, that not all investor groups use the help of analysts to make investment decisions and that some of them, naturally, have a solid financial/business background, and choose to perform these analyses themselves, to decide which stocks to buy/sell and when. So, we are looking at a wider group of AI-users on the side of the financial markets for this study.

Moreover, there are other relevant actors and entities involved in this complex relationship between companies, investors, analysts, consultants and AI (see fig. 2), such as ESMA (The European Securities and Markets Authority), an organisation which oversees all market transactions and enforces regulations. Its purpose is to improve investor protection and promote stable, orderly financial markets within Europe, alongside auditors, who verify the quality of a company's financial reporting, as well as the compliance with market regulations (ESMA & Seidenstein, 2023). These two actors work together to make sure that the general economy and the financial markets in Europe are as efficient, transparent, and well-regulated as possible, so they are relevant to this research too. In some of the papers, which will be discussed in this literature review, regulatory compliance is a considerable topic of discussion and without understanding who is responsible for checking and enforcing this compliance, it is difficult to imagine the issues related to this topic and the way in which they could be solved.

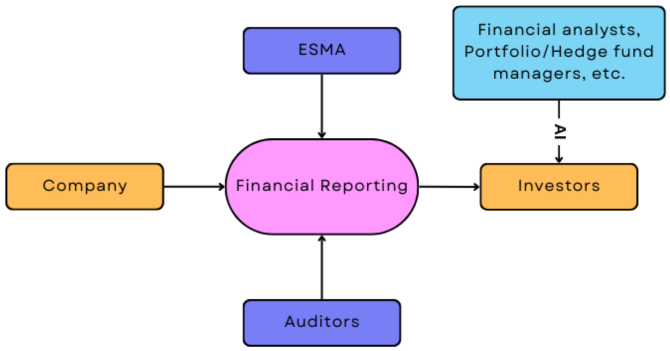

Figure 2: Actors and relationships in this research

When it comes to the second part of the topic (i.e. the company side, so the left side of the graph above), no relevant research could be found on how the above-mentioned listed companies react to this emerging change in the financial market, and the challenges and considerations this implies for them. Thus, this aspect will not be covered in the literature review. Nevertheless, it will be one of the main focus points of the research itself, so hopefully, after months of work, that aspect of financial reporting will not be a complete mystery anymore and will be covered well in the discussion/conclusion section of this paper.

2.2 From theory to practice: The interplay between external actors, AI and financial reporting

Having established the theoretical framework and identified the key actors and research gaps, the focus of this review will be shifted towards the practical implications of AI integration in the realm of financial reporting and auditing, where it has brought about significant transformations. This section reviews two key papers that inform the theoretical foundation of this research on how companies in the Netherlands are responding to AI-driven challenges in financial reporting. These papers provide valuable insights into the roles of AI, data analytics, and auditing practices.

Estep, Griffith, and MacKenzie (2023) explore how financial executives react to the implementation of AI in financial reporting and auditing. Their study emphasises how AI can both enhance efficiency and create complexity. They discover that AI can greatly improve the precision and efficiency of financial reporting and auditing procedures. Nevertheless, it presents several considerable obstacles as well, like the requirement for senior executives/managers to gain a more thorough comprehension of AI technologies and the possible dangers of excessive dependence on automated systems. The research shows that as AI enhances financial information accuracy, it also requires increased alertness and new expertise from financial experts. Executives must find effective ways to navigate the complexities of implementing AI, including correcting biases in algorithms and ensuring accurate interpretation of AI results. These results are essential for comprehending the wider implications of AI on financial reporting quality and the strategic changes needed by firms.

Expanding on this idea, Austin et al. (2021) explore how auditors, managers, regulatory bodies, and technological advancements in data analytics and AI interact with each other. Their research highlights the fact that the quality of audits can be greatly improved by AI and data analytics, which increase the precision and speed of examining financial data. Yet, they also emphasize the difficulties auditors encounter in adjusting to new technologies, pointing out the significant learning curve that necessitates ongoing education and skill enhancement. Like Estep, Griffith, and MacKenzie, this research cautions about the dangers of relying too much on AI, which can lead to blind spots if not properly handled. Emphasising the need to combine automated processes with human supervision is crucial for maintaining the quality of audits, offering insights that are directly applicable to my research.

Together, these studies strengthen the theoretical basis of this research by offering a thorough comprehension of the complex relationships on the left side of figure 2, so among technology, auditors, and the quality of financial reporting. Estep, Griffith, and MacKenzie (2023) point out that AI plays a dual role in financial reporting and auditing, serving as both a facilitator and a source of complexity, whereas Austin et al. (2021) highlight the advantages and obstacles of AI and data analytics in auditing.

This research, on the other hand, investigates how companies in the Netherlands address the challenges of AI readership in financial reporting, as they are the one actor whose story was not told yet. However, in order to do so it must first review all the relevant existing literature, understand the ideas and findings in it, and find patterns that would help deduce the ways in which companies would react to AI integration on the side of the financial markets, based on the ways that other actors react to this emerging phenomenon (ex.: financial executives or auditors, as well as investors). By managing that and designing a detailed qualitative survey, the study aims to enhance knowledge of how AI impacts financial reporting practices by studying the strategic changes companies make to address AI-driven challenges. If it succeeds, it has the potential to educate various parties, such as financial experts, authorities, and investors, on the everchanging applications of AI in the analysis of financial reports and financial reporting itself, and the steps required to ensure precision, dependability, and openness.

2.3 Various applications of AI in investment decision-making

To deepen our understanding of AI's role in other areas of finance outside of the internal environment of companies, this section will contour its various applications in investment decision-making. This section begins by examining the reasons why companies produce financial reports, their importance, and the methods financial analysts and investors use to extract valuable information from these reports.

Financial statements are crucial documents that offer a thorough overview of a company's financial health and performance. Created to ensure adherence to regulations, promote transparency, and facilitate investor communication, these reports are vital in overseeing and regulating corporate governance, according to Brigham & Houston (2019) and Solomon (2020). Yearly, bi yearly and quarterly updates, as well as frequent conference calls, provide stakeholders with precise and timely details on the company's activities and financial status (Tricker, 2019). This data allows them to evaluate the company's advancement compared to its business strategy, identify the requirement for more resources, and prepare for future strategic steps.

Moreover, the financial reports provide a thorough analysis of various financial statements, such as the income statement, balance sheet, and cash flow statement, which aid stakeholders in assessing the company's profitability, liquidity, and overall financial health (Wild & Subramanyam, 2015). Usually, they include quantitative elements (metrics and indicators) as well as qualitative elements. The latter give meaning to the numeric data and give more weight to performance indicators, that cannot be easily quantified, such as employee happiness. Financial reports provide a comprehensive perspective on the company by incorporating these factors and helping stakeholders make informed choices.

Traditional methods for assessing a company's profitability and financial health involve analysing relevant financial statements to find revenue and sales growth, profit margins, earnings per share (EPS), and return on investment (ROI%) (Subramanyam, 2014; Hayes, 2024). However, due to the vast number of companies that stakeholders would have to review to make informed investment decisions, and the substantial amount of time this would take, AI has become a common tool for investment decision-making in the 21st century. AI offers vast applications that can provide accurate results in a timely manner, significantly reducing opportunity costs (Davenport & Ronanki, 2018; Shen & Xu, 2020). This technological advancement enables analysts to process vast amounts of financial data efficiently, thereby enhancing decision-making capabilities in the financial markets.

One primary application of AI in investment decision-making is text and data mining. This involves extracting and clustering data from financial reports, news articles, and social media to identify patterns and insights that would be challenging to detect manually (Gazali et al., 2020). Figure 3 from Ren (2021) outlines this process in detail. Through data mining, AI systems can analyse large datasets, identify trends, and provide a comprehensive overview of market conditions, thereby facilitating more informed investment decisions.

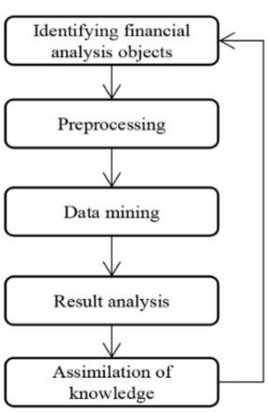

Figure 3: Data mining process in financial analysis and management

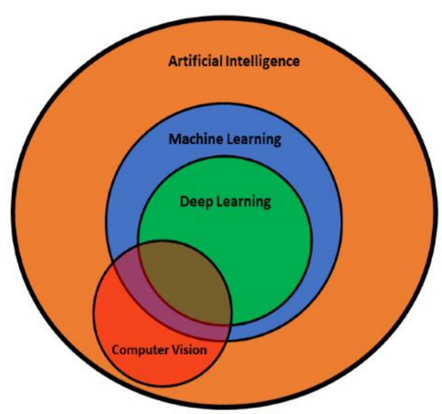

Figure 4: The relationship between AI, ML and Deep learning

Following text and data mining, sentiment analysis is another important AI application. Sentiment analysis uses text data from different sources to measure market sentiment towards particular stocks or companies. This approach includes evaluating the mood and circumstances of data to establish if the market sentiment is optimistic, pessimistic, or neutral. This analysis enables investors to forecast market shifts and make decisions influenced by the current market sentiment. For instance, a positive sentiment could indicate a favourable moment for purchasing, whereas a negative sentiment could suggest a possible decline (Gazali et al., 2020). Investors gain a major advantage in the market by rapidly analysing extensive qualitative data.

Forecasting future market trends and asset performance is another relevant use of predictive analytics. AI algorithms can accurately forecast future stock prices, returns, and market volatility by analysing historical data. These forecasts allow investors to predict market fluctuations and spot lucrative investment prospects in advance. Machine learning models, such as neural networks and decision trees, excel at identifying intricate patterns and nonlinearities in data that may be overlooked by conventional analytical techniques (Blitz et al., 2023).

Algorithmic trading is a different area where AI plays a crucial role. AI-driven trading systems utilise algorithms to determine optimal times for asset trades to achieve maximum returns and mitigate risk. These systems are able to make trades at the best moments, leveraging live market information and predetermined standards. For instance, companies such as ING utilize AI technology to observe the market for untapped investment possibilities, guiding their algorithmic trading tactics. This decreases mistakes made by people, reduces expenses, and enhances effectiveness in carrying out transactions (Blitz et al., 2023).

Machine learning (ML), which is a form of artificial intelligence (see fig. 4 above), has also significantly transformed quantitative asset management. ML algorithms can analyse vast amounts of financial data, uncovering patterns and relationships that might not be evident through traditional methods. This capability enhances the accuracy and effectiveness of investment strategies. For instance, ML is used in predictive modelling to forecast asset performance measures such as returns and volatility. Neural networks and decision trees learn from historical data, improving the precision of market predictions and investment decisions (Blitz et al., 2023).

Additionally, machine learning algorithms play a key role in risk management. Identifying and mitigating different types of risks, such as market, credit, and operational risks, can be achieved by detecting patterns and anomalies in financial data. Utilizing these ML risk models in investment strategies improves portfolio steadiness and robustness, defending against unfavourable market conditions (Blitz et al., 2023).

In portfolio optimization, ML is used to create portfolios that weigh risk and return according to investors' goals and limitations. Methods such as genetic algorithms and reinforcement learning use varied datasets to improve portfolio allocation strategies. This flexibility enhances productivity and guarantees resilience in evolving market circumstances (Blitz et al., 2023).

It is important to mention that although AI and ML offer great potential for making investment decisions, there are still numerous obstacles to overcome. These issues encompass data quality, interpretability of models, overfitting, bias in algorithms, and adherence to regulations. And finding solutions for these challenges is vital for guaranteeing the strength and trustworthiness of investment strategies powered by AI.

Despite that, the use of such algorithms in financial markets is growing, which highlights the significance of comprehending their functionality and their influence on investment choices, one of the main focuses of this study. Without understanding how AI influences the decision-making process of investors and how that could impact listed companies, we cannot study and comprehend how companies will react to this in return.

2.4 The side of companies: Corporate disclosure in the age of AI

Since the broader topic and all the relevant relationships have been covered in the previous paragraphs, it is time to delve into some specific aspects of the phenomenon of AI integration in the investment decision-making process of stakeholders. We will begin with the work of Cao, Jiang, Yang, and Zhang (2020), in which they delve into the intricacies of corporate disclosure in the age of AI. The paper investigates how companies communicate in a context, where machines are actively listening. It raises questions about the dynamics of communication between corporations and AI systems, where one party makes financial information (in the form of financial statements) open to the public eye and, in the hands of investors, the second one reads, analyses, and interprets it.

This form of communication (through various channels, such as regulatory filings, conference calls, company presentations, etc.) between firms and investors is more complex than it seems, because of the feedback effect and the way that a machine, that is supposed to think like a human would, gives recommendations and interprets everything. The feedback effect is, in simple terms, "how companies adjust the way they talk knowing that machines are listening" and it is imperative to this research, as it will help with assessing the extent to which companies, located in the Netherlands, adapt their financial reporting, knowing that investors use AI to read it.

According to the paper, "firms avoid words that are perceived as negative by computational algorithms, as compared to those deemed negative only by dictionaries meant for human readers", which is the main cause for the emerging trend of financial reporting bias, a phenomenon of great interest for this research. By fearing the way investors might read into the financial information provided by the company, its representatives adjust their way of writing and speaking, which makes the information conveyed less objective. That makes the issues of information manipulation and wrongful signalling from the side of the companies, and information misinterpretation by algorithms an even more relevant subject of discussion. After all, a company is all about its story and the numbers that it registered over the years. And if an investor can get to know that story and give it some weight in their decision-making, an algorithm can sadly not, so it will provide a purely number-driven recommendation, which can be damaging for the company, because numbers are not everything.

2.5 AI and the shift in corporate communication

Moving on to a more recent paper on the topic, Cao et al. (2023) provide a new perspective, which is goes deeper into the theoretical concepts that the previous paper brought to light. Their research investigates the role of AI in shaping the content and style of financial reports, signalling a paradigm shift in corporate communication. This study empirically investigates the possibility that with rising machine readership of corporate financial statements, which are time-consuming and costly to process by financial statements readers, managers may have less incentive to engage in financial misreporting. Therefore, it finds a reduction in financial misreporting when machine readership is higher. That means that machine readership has a disciplining effect on financial reporting and that it makes the financial markets more efficient (ex.: by making trades happen more quickly, due to the added trust that investors have in the information provided), improving investors' welfare.

Additionally, increased machine readership makes the companies' reporting more standardised, organised and transparent, increasing the quality and quantity of information available to investors and analysts. This consequently makes it easier and less costly (i.e. cost of acquiring information) for them and for in-house specialists to compare the financial statements of a company over different periods, or against industry benchmarks to identify trends, anomalies, or deviations from expected norms. However, it does make the situation more difficult for the firms themselves, as they have to take more things into account and provide more details (i.e. incorporating narrative elements in addition to numerical data), when composing their regular financial reports, which can lead to several negative effects and disclosure costs, such as a loss of their competitive edge (Cao et al., 2021).

2.6 Ethical implications of AI use and recommendations

To make the discussion on the challenges that AI tools pose for firms complete, this literature review will also delve into Barocas and Selbst's (2016) examination of "Big Data's Disparate Impact", which provides insights into the ethical implications of algorithms, particularly in relation to fairness and discrimination. Understanding how biases may be ingrained in AI algorithms becomes crucial in the financial sector, where decisions can have significant societal and economic consequences. The key idea derived from this journal article is that although algorithms can eliminate human biases from the decision-making process, they are only as good as the data they work with, so their recommendations should not be thoughtlessly relied upon. As stated by Lipton (2016), "The black-box nature of many algorithms may hinder the user's ability to comprehend and trust the decisions made", so caution is advisable when it comes to taking advice from a machine, no matter how intelligent.

Therefore, there are two sides to the coin of corporate disclosure and financial reporting. On the one hand, more transparency, standardisation, clarity, and integrity are better for the financial markets and the companies themselves, as market participants will have the opportunity to make "good" and informed investment decisions, and the management of companies will tend to make less irrational and opportunistic investments decisions (Zhu, 2019). On the other hand, if a couple of investors misinterpret a decision or some words/numbers in the statement of a company, due to being subjective or overly relying on AI's advice, a firm's reputation can be ruined, which has considerable consequences on its viability (Mazzola et al., 2006). Herding behaviour is quite powerful even among rational investors, due to the human instinct to imitate and follow the crowd in a world of uncertainty, so if a couple sell their stock for any reason at all, the others will do the same without even surely knowing why (Keynes, 1930; Baddeley, 2010).

To sum up, this comprehensive literature review synthesises key insights from diverse perspectives on AI in corporate disclosure, financial reporting, and investment decision-making. The collective findings underscore the multidimensional impact of AI on business and finance, highlighting both opportunities and complexities associated with its integration. As artificial intelligence continues to evolve, these scholarly contributions serve as valuable resources for researchers, policymakers, and industry professionals navigating the dynamic landscape of AI in corporate and financial contexts. And while existing literature has provided valuable insights into the general aspects of the topic, a noticeable research gap persists, particularly in understanding the practical experiences, challenges, and considerations from the perspective of companies actively engaged in AI-analysed financial reporting processes. This is where this survey-based research comes in, attempting to fill this gap with new insights from financial workers in the Netherlands, some of which have to deal frequently with algorithmic scrutiny in their work.

3. Research hypotheses

After determining the research focus of this graduation work and reviewing the most relevant current literature on this topic, it is time to define some research hypotheses, based on the theory and findings of the papers discussed above. The following hypotheses cover various dimensions of the complex research question addressed in this paper, providing a well-rounded approach to exploring the impact of AI on financial reporting and addressing the emerging challenges and considerations for companies. However, due to the exploratory nature of this research, they will only have a guiding role for the survey and not be tested, as the focus here is on the observations/data that will be gathered from the respondents.

Hypothesis 1: As AI tools become increasingly integrated into the financial sector, companies alter their financial reporting strategies to cater to machine readership. This consequently creates a shift towards more standardised, detailed, but also positively biased and time-consuming reporting practices.

This hypothesis builds upon the insights from Cao et al. (2020) and Cao et al. (2023), suggesting that companies adapt their communication styles and content in financial reporting to accommodate machine readership. It proposes that this adaptation may lead to a reduction in financial misreporting, but could also introduce biases and challenges related to transparency, integrity and required effort in financial disclosures.

Hypothesis 2: Due to the growing integration of AI tools in the analysis of financial reports, several risks and challenges for companies arise, including issues related to misinterpretation of financial information and overreliance on algorithms from the side of investors.

This hypothesis is based on the insights from the works of Cao et al., 2021, Mazzola et al., 2006 and Barocas and Selbst’s (2016), in which the authors discuss some of the major shortcomings of AI-usage, which can make things difficult for companies. For instance, AI is not as transparent and explainable, as it should be, and it is also not error proof, so it could give investors negative investment advice regarding a company, that is actually good and profitable. The moment those couple of investors start selling their shares in that business or simply not investing in it at all, others will do the same, which could ruin the company’s reputation in then financial market and negatively influence its profitability.

4. Research methodology

The research methodology employed in this study is designed to address the research questions and the above-formulated hypotheses effectively, focusing on the impact that AI integration on the side of the market has on the way that medium, but mostly large, listed companies in the Netherlands report their financial information. The size of the company matters here, as investor groups do not usually use AI to analyse the financial reports of SMEs.

4.1 Research Method and Motivation

Prior studies investigating the effects of integration of AI tools on financial reporting have utilised a quantitative analysis to explore the prevalence, impact, and challenges associated with AI adoption in this domain. However, they do not reflect the opinions and experiences of the affected companies on the topic, as they are faced with an increased level of machine readership. This study adopts an inductive, survey-based approach comprising a comprehensive questionnaire with a couple of detailed, qualitative questions, designed to capture that information directly from the source. And the survey itself will be designed with the help of a couple of guiding books and academic articles on the best ways to create insightful surveys for social research.

In addition to that, the insights that this research tool aims to generate through the qualitative questions asked are as follows: *Do companies know about the increasing use of AI from the side of investors and analysts to read their financial information?; If they do, what are they currently doing about it and/or planning to do in the future?; What do they think are useful internal mechanisms, that could prevent AI from having a negative effect on their financing operations and reputation?; What regulations do they think should be in place to enforce responsible and ethical AI use?*. Finding answers to these questions could form the base of future research projects, investment decision-making guidelines, business and regulatory practices, therefore, every bit of information gathered from the respondents is of relevance here.

Before this section goes any further, it is paramount that two things are clarified: why an interview approach was not chosen for this study and why it is an inductive, instead of a deductive one. To shed light on the first part, a survey was chosen for this research over conducting interviews for several reasons. Firstly, the topic is sensitive and companies may not be willing to discuss it openly with external parties, unless necessary. Surveys provide anonymity, encouraging more candid responses. Therefore, respondents can discuss the issues addressed in the survey in an open and safe way, which makes them more willing to participate in the study. Secondly, time constraints make surveys a more practical option. While interviews can take an hour or more, surveys typically require only 10-15 minutes, which can already be much for some company employees, due to the busyness of the world we live in. Lastly, if designed well, surveys can gather almost the same essence as interviews, but with a higher response rate, which allows for a better overview of the different range of experiences that employees have with financial reporting practices. And it makes it easier to gather more information and opinions on this unresearched matter.

Subsequently, the inductive research method was chosen for this study due to its exploratory nature. It is not the traditional kind of research, where a well-made regression analysis could test the hypothesis/assumptions, formulated before the research was even conducted, and answer the research question. To answer the research question posed in this paper, lots of data would have to be gathered and categorised to find patterns, that were not initially assumed. So, this research starts from data and goes to theory (hence the exploratory part), while the deductive, more quantitative and structured kind of research, starts from focused questions and hypotheses, and then investigates the data gathered to try and test/prove them. The hypotheses from the previous section are in this case guiding, as they help with keeping a focus while making the survey and processing the data. However, they will not be directly tested, like they would be in quantitative or deductive research.

4.2 Sample Characteristics

Furthermore, the primary data source for this study will be the survey responses collected from financial workers (i.e. financial managers, accountants, etc.), activating in listed companies, that operate in the Netherlands, or working for them (i.e. in accounting and consultancy firms, to which bigger firms have outsourced their financial reporting). This is the geographic location of choice for this research, because of the vast number of successful companies it managed to nurture over the years, its thriving culture of innovation and due to it being a harbour for investments from all over the world. Also, based on the data from the Dutch financial market authority, for example, 75% of all the trades made on the equity market in the past years were algorithmic (AFM, 2022), meaning that this financial market is the right one for this research.

Additionally, the goal is to gather as many responses as possible from this target group, to extract relevant insights into the topic. However, it is expectable that the sample size will be modest, but suitable and sufficient for this research, due to a number of reasons. Firstly, due to the confidential and sensitive nature of the topic, companies may be hesitant to openly discuss their practices. Thus, gathering any number of complete responses is something of value not only for the academic community, but for the broader international one as well. Secondly, the targeted sample size aligns with the exploratory nature of the study. Qualitative research, such as this inductive survey-based approach, prioritizes depth of understanding over statistical representativeness. With well-structured qualitative questions, each response can yield rich insights into the challenges, adaptations, and strategic considerations specific to AI integration in financial reporting.

Finally, given resource constraints and the specialised expertise required of respondents, a smaller, yet focused sample size is both practical and sufficient for capturing diverse perspectives and experiences within the targeted industry segment (i.e. financial services). This approach ensures that the research can effectively explore emerging themes and provide nuanced insights that contribute to the evolving discourse on AI in financial reporting practices.

4.3 Survey Structure, Purpose and Measurements

When it comes to the survey itself, it will be sent for ethical approval before being used and designed to capture in-depth quantitative data, to provide a comprehensive understanding of how AI integration by investors and analysts affects financial reporting practices. Therefore, several multiple choice and open questions will be included in it. And although most of the questions in the survey ended up being MC questions, due to the time constraints (i.e. a survey should not be longer than 10-15 min) and the dropping response rate with each additional open question (Vogt, Gardner, & Haeffele, 2012), open questions had their important place in it too.

In order to keep the survey length to a minimum and be as specific as possible, they were placed at strategic points in the questionnaire, which gave the registered answers more context and depth. For instance, after asking the respondents whether their financial reporting practices have improved over time due to machine readership and providing them with answer options, they were asked to briefly tell the reasons why they felt or thought that way. This resulted in a deeper understanding of these changes, which is more meaningful than the initial answer alone would have been.

Moreover, the survey questions are divided into six sections, which cover both the research question(s) and the hypotheses: General Information, Awareness of AI Integration and Risks Posed by It, Adaptation of Financial Reporting, Challenges Faced and Ways of Overcoming Them, Strategic Considerations, and Prevention and Avoidance of Negative Effects.

Section 1: General Information

This section collects demographic data about the respondents, including their industry sector and role within the company. This information will help contextualise the responses and analyse variations in results across different sectors and positions.

Section 2: Awareness of AI Integration and Risks Posed by It

The respondents' awareness of AI tools used by analysts and investors, as well as their concerns about potential risks, are evaluated in this section. It is mostly made up of open-ended and multiple-choice questions for capturing qualitative insights, but it also contains one closed-ended question, which leads to a couple of additional in-depth inquiries on the topic. An example of a key MC question in this section is the following: “What risks do you see associated with the use of AI by investors and analysts in analysing the financial information of companies?”. This one was designed to address existing theoretical knowledge, thoroughly illustrated in the literature review section (i.e. through options, such as “overreliance on algorithmic output/recommendations from the side of investors, who then neglect traditional financial analysis methods and human judgment”), research one of the main hypotheses (i.e. hypothesis 2, based on the second research question of this study) and extract new insights from the respondents, so it is of key importance.

Section 3: Adaptation of Financial Reporting

In response to the risks posed by AI integration, survey participants are asked about the changes their companies have made to their financial reporting practices. This section consists of open-ended questions, to explore additional, unlisted strategies, and multiple-choice questions with options for specific adjustments deducted from theory (ex.: one choice is: “the reports are more carefully written to avoid a negative interpretation of words”). That way, the key theoretical concepts from the literature review section can be tested for a different environment (the one of companies in the Netherlands) and the hypotheses/deductions depicted above can be addressed. Moreover, by collecting data from the questions in this specific section, more than half of the mystery that the first and main research question is attempting to unravel, can be resolved.

Section 4: Challenges Faced and Ways of Overcoming Them

Moving forward in the survey, the second research question will be addressed. This section explores the challenges companies face when adapting their financial reporting practices to accommodate AI readership. Respondents can select from a list of common challenges (ex.: balancing narrative and numerical reporting) and provide detailed descriptions of additional challenges they have encountered through open-ended questions. They are also asked how their companies have/are planning to overcome these challenges, providing valuable insights into best practices and strategic considerations.

Section 5: Strategic Considerations

Based on the risks and challenges the respondents selected and discussed in the previous sections, they are further asked about how concerned their organization is about the possible implications of AI misinterpretation of their financial data. Multiple-choice and open-ended questions are included in this section, to derive in-depth answers about the concerns that companies might have, in addition to the strategic factors and key players they consider when creating their regular financial reports. One such question is the following: "What considerations (i.e. internal and external factors, players, etc.) does your company take into account, when adapting financial reporting practices in response to AI integration by investors and analysts?". It should aid in understanding the whole picture of the relationship between the use of AI by investors and a company's financial reporting strategies. A picture which is not covered in any modern literature, but which could help this study build a new theoretical framework.

Section 6: Prevention and Avoidance of Negative Effects

This last section addresses broader questions about preventing and mitigating the negative effects of machine readership. Respondents are invited to suggest internal mechanisms, such as company strategies and policies, as well as the role of external mechanisms, such as regulatory institutions, in mitigating these effects. This could help other companies in the industry, as well as regulators, in dealing with the negative effects of AI integration on the side of the financial markets.

4.4 Data Collection and Analysis

As mentioned previously, the survey will be distributed electronically to financial workers in medium to large, listed companies in the Netherlands or firms that they outsourced their financial reporting to. Hence, to achieve a representative sample, it will be sent specifically to companies in the financial services and consulting industry, and to employees with various roles, related to financial reporting activities, within those companies. The estimated response rate is of 13 complete surveys, which will ensure sufficient data for analysis due to the qualitative nature of the survey and its many open questions, and the small population of large corporations in the Netherlands, a country in an economic are where 99% of companies are SMEs (Small and Medium-sized Enterprises | Fact Sheets on the European Union | European Parliament, n.d.).

Furthermore, the responses will be collected over the time span of two to three weeks and made anonymous, to respect the privacy of participants. The accumulated qualitative data will further be analysed, using the inductive approach described above and the smart tools provided by Qualtrics, to identify patterns and extract useful insights from the experiences of the respondents. This exploratory approach will provide a good base for answering the research question(s) and verifying the initial hypotheses, which should together open the door to the currently unknown details on the side of companies.

To recapitulate, the inductive, survey-based approach adopted in this study aims to explore the impact of AI integration by investors on the financial reporting practices of medium and large, listed companies in the Netherlands. By directly capturing the opinions and experiences of financial workers, this methodology provides a comprehensive understanding of the challenges, adaptations, and strategic considerations in this evolving landscape. The findings from this research will contribute valuable insights into the implications of AI in financial reporting, guiding future practices in the field and regulatory considerations.

5. Findings and Limitations

The purpose of this study was to investigate how the integration of artificial intelligence (AI) affects company financial reporting methods. The research involved a survey targeting professionals in finance, including financial officers, analysts, and accountants, to acquire information about their experiences and viewpoints on AI-driven financial analysis from the side of the financial markets. The findings reveal significant trends and illustrate both the benefits and limitations of using AI to analyse the financial reports of listed companies.

5.1 Research findings

1. **Awareness and Concern about AI Integration**: Prior to taking the survey, the majority of respondents (69%) were aware of the rising usage of AI tools by investors and analysts. This high degree of knowledge demonstrates the growing understanding of AI's importance in the financial sector, and it has driven firms to consider the adaptation of their financial reporting practices to cater to machine readership. This finding is consistent with the work of Cao et al. (2020) and Cao et al. (2023), who highlighted the growing reliance on AI in the financial sector and the way that companies might think about it (i.e. their concerns).

   Despite the increasing awareness among companies in the Netherlands and the expectations of prior research, concerns about AI deployment differ, with 62% of the participants expressing moderate concern and 15% expressing strong concern about the possible impact of AI-driven misunderstanding of financial information on firm reputation and financial performance. This discrepancy could arise from the difference in roles and levels of experience among the respondents, as well as their risk aversion and depth of understanding of the ramifications of the merging phenomenon this study is attempting to understand. The two respondents who had a strong concern about the effects of AI on their companies in the future, were also the ones to have the most proactive ideas in how to deal with them, which indicates an above average degree of knowledge of the topic.

2. **Impact on Financial Reporting Practices**: According to the survey results, AI integration has made financial reporting more complex (i.e. voluminous, specific, etc.) and time-consuming, as organisations attempt to achieve higher accuracy and detail standards. While 23% of respondents acknowledged improvements in their reporting techniques, these developments have come at the expense of more time spent working on the reports and their increasing complexity, confirming the first hypothesis of this research paper. This finding aligns with the sentiment that providing more detailed explanations and context to financial data has become necessary to ensure clarity for both human and machine readers.

   However, some participants seemed to think that these changes in their financial reporting practices are more a result of stricter regulations, increased regulatory oversight and frequent internal audits, than of machine readership. That could be due to a lack of awareness of the current impact that the increasing AI usage has on their companies, which is difficult to observe or measure, or due to the fact that it might not be as widespread at the moment as hypothesised, at least in Overijssel (a province of the Netherlands located near Germany). And that the expected effects are something to be observed and studied in the future.

3. **Risks Associated with AI Use**: In spite of that, there are several considerable risks of using AI in financial analysis, as perceived by the respondents, which include potential misinterpretation due to algorithmic biases or errors, as well as investors' overreliance on AI outputs, which may lead to a disregard for traditional financial analysis methods and human judgement. These concerns, which were accentuated by existing literature (ex.: the work of Estep, Griffith, and MacKenzie (2023)) and hypothesis 2, underline the importance of taking a balanced approach to employing AI, ensuring that it complements rather than replaces human expertise.

4. **Challenges in Adapting Reporting Practices**: The primary challenges identified include maintaining the transparency, accuracy, and reliability of financial data, while avoiding language that might be negatively interpreted by AI systems. Additionally, balancing narrative and numerical reporting and keeping the competitive edge of the company, while disclosing more information, were also significant concerns. These challenges highlight the nuanced adjustments companies must make to ensure their reports are both AI-friendly and comprehensible to human stakeholders.

5. **Considerations**: When it comes to the multitude of actors and factors, that companies have to take into account when adapting their financial reports and strategies to the emerging market phenomena, most survey participants indicated that the most important ones to consider are: the stricter regulatory requirements (92%), the accuracy and quality of financial information (85%), investor expectations and AI's perception of information, which is different from the one of human readers (77%).

   Despite the risks highlighted by Mazzola et al. (2006) in their study, only a small percentage of the respondents were concerned about maintaining the reputation and competitive advantage of the company, meaning that most of them stick to a careful, by-the-book and transparent way of making financial reports, instead of attempting to paint a different picture or keep crucial information away from the public. Also, they seem to be more interested in fulfilling all the regulatory requirements and investor expectations, than in the actions of their competitors, who have access to their financial information as well. These findings go against the expectations of Cao et. al (2021)'s research about the copycat strategies of competitors and how they incentivise companies to disclose less information out of fear of being taken advantage of.

6. **Adaptation Strategies**: Based on the insights from 12 of the 13 participants, their companies are not currently adapting their financial reporting practices, as that is, in their view, an issue for the near future. However, they are planning on implementing a variety of techniques to address these challenges, including providing more context to numerical data and words (ex.: through semantic tagging/labelling), as expected from the beginning of this research, and avoiding ambiguous language. Effective approaches also included training personnel about the implications of AI readership and carrying out internal audits to maintain reporting standards. These initiatives demonstrate a proactive approach to dealing with AI's effects on the financial reporting of companies and support hypothesis 1, emphasising the significance of clear, transparent, and consistent communication.

   It is important to mention that the one person, who said that their company is adapting its financial reporting, mentioned that their reports became more standardised and detailed, as the requirements for financial reports are stricter and more descriptive information (i.e. words and explanations) is needed in addition to numbers. They also emphasised the fact that their reports are written more carefully, to avoid a negative interpretation of the words used, which confirms hypothesis 2 of this study and the findings of Cao et al. (2020).

7. **The role of internal and external mechanisms**: At the end of the survey, participants were asked to come up with internal (ex.: company policies) and external mechanisms (ex.: rules and regulations), that might help diminish the negative impacts of AI use by investors and financial analysts. When inquiring about both types of mechanisms, the following predominant responses were registered, which were not expected in the beginning of this research project.

   <u>Internal Mechanisms</u>

   Respondents emphasised the need for comprehensive training programs to help employees better understand and utilise AI tools. For instance, one participant suggested that "training employees to work with AI and checking our own reports with this tool before making them available to investors" could help and be an effective defence mechanism, an opinion shared by 2 others. Another highlighted that "discussing the issue of machine readership with the accounting and financial teams to raise awareness and establish a set of best practices together" might be the way to cope with the issues presented by AI.

   These insights accentuate that raising awareness and investing in such training can enable financial teams to effectively address the challenges posed by AI, fostering open discussions and developing best practices tailored to the company's specific needs. Moreover, using AI to make sure that the data has enough context is another important recommendation, which can only be implemented after the employees are well-informed and trained.

In addition to that, transparent communication with investors about AI's role in financial reporting was also deemed crucial. Several respondents mentioned that transparent communication with investors on the topic and encouraging them to have humans review AI output is of key importance, as well as creating financial reports by the book and holding regular conference calls and Q&A sessions with investors. Therefore, the financial employees from this random sample believe that maintaining open communication and good financial reporting practices can help mitigate misunderstandings and enhance trust, which would reduce the need for investors to use the help of third parties and of AI tools.

Building on the idea of maintaining good reporting practices, 33% of the survey participants confirmed that adhering to existing standards and IFRS regulations, while being adaptable to new market conditions is essential. This ambidextrous approach ensures that financial reports remain consistent, reliable, and comprehensible to both human and machine readers, reducing the risk for potential misinterpretations and negative impacts on the performance of companies.

External Mechanisms

Respondents underscored the critical role of regulatory oversight in ensuring the ethical use of AI in financial analysis. One respondent remarked, "regulators are everything that stands between good and poor practices in the business/investment world", while others emphasised the need for ethical guidelines: “there should be ethical guidelines to AI use, some of which are legally enforced". Establishing and enforcing thorough regulations and standards can prevent issues arising from irresponsible algorithmic applications, protecting both companies and investors.

Moreover, mandating human oversight in AI processes was highlighted as another beneficial measure, with a respondent suggesting that "better regulating AI use by requiring users to keep a couple of humans in the loop could have a positive impact both for companies and investors". This would ensure that AI complements, rather than replaces human judgment, reducing the chance of algorithmic biases. Furthermore, monitoring investor behaviour was seen as crucial to prevent harmful practices, as one respondent pointed out: "regulators should oversee investors' activity as much as company activity to prevent them from overly relying on AI and damaging the reputation of a company without consequences". Supporting these regulatory improvements can truly help businesses protect their openness and uphold investor trust, leading to benefits for both sides, a more efficient financial market and increased social welfare.

Therefore, the incorporation of AI into financial reporting presents both opportunities and challenges. Even though AI can improve the precision and thoroughness of financial analyses and investment decision-making, it also brings about complications and the possibility of considerable ethical problems. Investors need to find a good balance between utilising artificial intelligence functions and maintaining human decision-making, while companies have to try to mitigate the risks from their side through solid internal mechanisms and the support of external ones. They could do that by conducting frequent internal audits, training their employees and finding effective communication strategies, all of which could help in preventing the negative effects of AI, that some investors did not manage to or simply ignored.

Moreover, following strict regulatory standards and supporting strong external oversight can help lessen the adverse effects of AI misuse. In the end, the key to effectively incorporating AI on the side of the financial markets (i.e. the investor side) lies in finding a balance between technological progress and human knowledge to guarantee that financial information is accurately analysed and presented, and that it can be trusted by everyone involved.

5.2 Limitations

Despite the novel and insightful findings, this study has several limitations that must be acknowledged:

1. **Sample Size and Diversity**: The survey sample was relatively small and may not fully represent the broader population of financial professionals. In addition to that, the respondents were primarily from specific roles within the finance sector (i.e. financial and accounting officers), which were crucial to financial reporting activities, and mostly from the financial service industry (85%), which could limit the generalizability of the findings to other professional contexts and industries.

2. **Geographic Scope**: The study focused on a limited geographic area (i.e. the Netherlands), which may not capture the varying impacts of AI integration across different regulatory environments and market conditions. Future research should aim to include a more diverse set of geographical regions, such as the multitude of countries from the European continent, to provide a comprehensive understanding of these differences.

3. **Temporal Constraints**: The survey's cross-sectional design provides a picture of present practices and perspectives, but it fails to account for the dynamic and developing nature of AI technology, as well as its long-term implications for financial reporting. Longitudinal research would be useful for understanding these long-term effects.

4. **Qualitative Depth**: The survey collected thorough qualitative data on the prevalence and impact of AI integration, but it could have lacked a bit of the depth that interviews or case studies could provide. These other qualitative methodologies may provide more details into the specific strategies and challenges that businesses encounter, so they should be explored in future research projects.

6. Theoretical and practical contributions

Despite briefly mentioning the contributions of this study in previous sections, they will be discussed at greater length here. This study makes both theoretical and practical contributions to the existing body of knowledge of how artificial intelligence (AI) is integrated into the financial sector, with a focus on the effects on firm's financial reporting. From a theoretical standpoint, this study contributes to the process of unravelling the complex connections between AI tools and financial reporting practices, while from a practical standpoint, it gives valuable insights for industry practitioners (i.e. business professionals) and legislators.

6.1 Theoretical Contributions

1. New Conceptual Foundation for Financial Reporting in the era of AI

A new conceptual framework is introduced through this research, that illustrates the way in which the increasing use of AI tools by investors influences the financial reporting practices of companies. Unlike earlier studies, that primarily explore AI capabilities in isolation (within companies or in making investment decisions), this framework connects the mechanisms of AI analysis with the strategic responses of companies (ex.: semantic labelling, offering more context to numbers, working with AI in their own internal audits, etc.), highlighting the adaptive behaviours in financial reporting. This framework also links a complex network of actors with distinctive roles and integrates theories from financial accounting, AI, and corporate strategy, offering a robust model for future research.

2. Timely critique of less recent existing literature

Despite the risks highlighted by Mazzola et al. (2006) in their study, only a small percentage of the respondents were concerned about maintaining the reputation and competitive advantage of the company, meaning that most of them stick to a careful, by-the-book and transparent way of making financial reports, instead of attempting to paint a different picture or keep crucial information away from the public. Also, they seem to be more interested in fulfilling all the regulatory requirements and investor expectations, than in the actions of their competitors, who have access to their financial information as well. These findings go against the expectations of Cao et. al (2021)'s research about the copycat strategies of competitors and how they incentivise companies to disclose less information out of fear of being taken advantage of.

3. Detailed Exploration of AI-Induced Challenges

The study systematically identifies and categorises the emerging challenges companies face due to AI's role in financial analysis. These challenges include:
<u>Increased Reporting Complexity</u>: Companies must now consider AI algorithms' ability to analyse and interpret their financial statements, leading to more detailed, structured and time-consuming reporting practices.

<u>Bias and Misinterpretation</u>: Due to their black box nature, AI tools have the potential to introduce biases in financial analysis, potentially impacting the reputation and financing activities of a company, as well as the investment decisions of actors in the financial market.

<u>Regulatory Compliance</u>: The current regulatory frameworks have strict rules directed toward the financial reporting practices of companies, however, there are little rules that ensure responsible AI use of the side of investors. That is quite challenging for companies, as they have to adhere to so many norms in their activities, while investors do not.

6.2 Practical Contributions

1. Guidance for Financial Practitioners

On the practical side of things, the findings of this research provide significant recommendations to financial managers, accountants, and other practitioners. Understanding how AI systems read and understand financial reports could help these professionals adapt their reporting practices to avoid misinterpretation and bias (for example, by incorporating NLP techniques and semantic tagging). This knowledge is critical for ensuring that AI technologies accurately understand the information presented, preserving the integrity and credibility of financial disclosures.

2. Recommendations for Policy and Regulatory Developments

For policymakers and regulatory agencies, such as the European Securities and Markets Authority (ESMA), this research emphasises the need for an updated legislation and guidelines, that address the ethical implications and potential biases brought by AI in investment decision-making, and financial reporting activities. Recommendations include creating standards for AI readability in financial reports, along with increasing transparency and human oversight in algorithmic decision-making processes. These approaches can help mitigate the risks associated with overreliance on AI tools and improve the functioning of the financial markets.

3. Improving Investor Decision-Making

This study also assists investors/investment groups in better understanding and interpreting financial information, by providing insights into how AI algorithms assess financial statements. This can lead to better informed, more ethical and profitable decisions, lowering the possibility of errors and opportunity costs (i.e. the potential forgone profit from a missed opportunity (Fernando, 2024)). Furthermore, the study's results on the biases and limitations of AI-generated predictions serve as a warning to investors, advising them to use AI tools responsibly rather than relying on algorithmic outputs alone.

4. Aiding the design of new Investment and Corporate Strategies

Additionally, investors can use the findings of this study to design strategies that balance the benefits of AI integration with the necessity for continued human monitoring and judgement. Companies, on the other hand, would be encouraged to openly communicate with investors and implement best practices for financial reporting, outlined in this paper, that take into account both human and artificial intelligence readers. Thus, improving the clarity, accuracy and value of financial disclosures, and building the foundation of a strong stakeholder relationship based on trust.

5. Future Research Directions

Finally, this research opens up various areas for further exploration. Hence, subsequent research could dive more into the precise algorithms adopted by various investment groups, as well as their respective effects on financial reporting. Also, broadening the geographical reach outside the Netherlands and incorporating a wider variety of industries may provide a more thorough understanding of AI's impact on global financial reporting. Therefore, this could be something for a group of researchers with more time and resources to attempt in the future.

In conclusion, this research project manages to advance both theoretical knowledge and practical applications related to the integration of AI on the side of the financial markets. By addressing the complexities and challenges associated with this emerging phenomenon, the study provides a solid foundation for future research and offers actionable insights for practitioners and policymakers, contributing to a more efficient, transparent, and ethical financial market.

7. Future research recommendations

Expanding on the results, contributions and recognising the constraints of this research, various paths for future studies can be pinpointed to improve our comprehension of the impact of AI integration on financial reporting and to investigate the detailed consequences of this technological change.

Future studies should strive to expand their sample size and diversity of financial experts to enhance the applicability of the results. Broadening the survey to include a wider variety of positions in the financial industry, along with including participants from connected areas like auditing, regulatory bodies, and corporate governance, can offer a more thorough outlook on AI implementation. Moreover, involving individuals from different sectors aside from finance can unveil unique challenges and opportunities specific to each sector, enhancing the collective knowledge of how AI affects financial reporting.

In addition to that, future research should expand its geographic coverage to encompass the impact of regional regulations and market conditions on financial practices. Cross-national studies with participants from varying countries and regions can demonstrate how local laws, cultural views on technology, and market forces impact the utilisation and success of AI in financial reporting. This research could uncover effective strategies and provide understanding on how multinational companies can successfully integrate AI technologies in various settings (Leuz, Nanda, & Wysocki, 2003).

Although the current study's cross-sectional design offers a glimpse into modern practices and opinions, understanding the constantly changing AI technology and its long-term effects necessitates longitudinal research. Observing trends, adaptations, and the long-lasting impact of AI on financial reporting can be achieved by tracking changes over time. Long-term research can also shed light on the gradual changes companies make as AI tools advance and are more commonly used (Brynjolfsson & McAfee, 2014).

Aside from that, using qualitative methods like detailed interviews, group discussions, and case analyses may provide a more comprehensive insight into the challenges of integrating AI. These approaches are able to reveal in-depth stories and concrete instances of how businesses are adjusting their reporting methods, the obstacles they encounter, and the tactics they use to address these hurdles (Yin, 2017). Such qualitative studies can offer detailed, contextual information that quantitative approaches might miss, providing a deeper understanding of the human and organisational aspects involved (Patton, 2015).

As artificial intelligence becomes more prevalent in financial reporting, the significance of ethical and regulatory factors grows. Future research needs to investigate the ethical consequences of using AI, including matters of prejudice, openness, and responsibility. Studying how companies and regulatory bodies deal with these issues can offer insight for ethical deployment of AI in financial analysis (Moor, 2006;

Binns, 2018). Furthermore, assessing the changing regulatory environment and its influence on the integration of AI in financial reporting can pinpoint where policy interventions may be necessary to guarantee ethical AI usage.

Also, the quick advancements in AI technology result in continuous improvements in functionality. Future studies need to stay up to date with these technological advancements, investigating the impacts of new AI tools and innovations on financial reporting. Research on recent AI advancements, like natural language processing, machine learning algorithms, and predictive analytics, can offer a deeper understanding of how these technologies are being incorporated, as well as their possible advantages and disadvantages. Comprehending these developments can assist businesses in remaining at the forefront and using AI more efficiently in their financial reporting procedures.

In conclusion, incorporating multidisciplinary techniques can enhance the comprehension of how AI affects financial reporting. Partnerships among finance, computer science, ethics, and legal studies can offer a multilateral, deeper perspective on the obstacles and benefits linked to AI incorporation. Interdisciplinary research can lead to creative solutions that tackle the diverse aspects of implementing AI, ensuring that financial reporting practices stay strong, clear, and reliable amidst technological advancements.

By following these suggestions, upcoming studies can create a deeper and more detailed comprehension of the impact of AI integration on financial reporting. This will not just add to academic understanding but also offer actionable advice for financial experts, firms, and policymakers dealing with the intricacies of AI in finance.

8. Discussion and Conclusion

8.1 Discussion

The findings of this study have several broader implications, touching upon ethical, legal and societal issues, that extend beyond the immediate scope of financial reporting. These considerations are crucial for a holistic understanding of AI's impact on the financial sector and its stakeholders.

Artificial intelligence’s use in the analysis of financial reports raises ethical concerns related to fairness, accountability, and transparency. Relying on AI algorithms can reinforce current biases, if the data they are based on is not entirely trustworthy. This might result in unfair consequences, like discriminatory loaning practices or prejudiced investment recommendations (Binns, 2018). Hence, ethical AI guidelines require a thorough examination of data inputs and algorithmic outputs, to guarantee fairness and reduce bias as much as possible (Barocas, Hardt, & Narayanan, 2019). Furthermore, according to Floridi et al. (2018), it is crucial for companies and investors to be transparent about the use of AI tools and the rationales behind their decisions, to uphold trust among stakeholders and ensure harmonious, mutually beneficial interactions among them.

Legal challenges are also presented by incorporating AI into investment decision-making. Laws and regulations have not evolved fast enough to keep up with the rapid progress of AI technologies, resulting in a regulatory gap. Therefore, new and updated laws are urgently required to regulate AI's involvement in both financial reporting and analysis, to guarantee responsible and ethical usage (Calo, 2017). Legal guidelines also need to be put in place to regulate the transparency, accountability, and accuracy of in financial disclosures, which could be of a different nature due to the increasing use of algorithms on the side of the financial markets. This involves creating better auditing standards for financial reports generated by people, as well as AI, as that will likely be a tendency in the future, establishing clear rules for investment decision-making aided by algorithms and implementing effective mechanisms to ensure accountability for mistakes or biases caused by AI, and their outcomes (Wagner, 2018).

On a societal level, the extensive use of AI in finance can have significant effects on job availability and skill demands. With the automation of basic financial analysis tasks, there could be a shift in employment, especially in roles that require manual data processing and fundamental analytical skills (Autor, 2015). This involves changing educational and training programs to provide the workforce with the necessary skills for the changing financial environment (Manyika et al., 2017). Furthermore, it is important for society to make sure that the advantages of AI are distributed evenly and do not make current inequalities worse. Public policies should be directed towards helping individuals, who are negatively impacted by the changes brought about by AI in the financial industry (Brynjolfsson & McAfee, 2014).

To sum up, this research emphasises the game-changing possibilities of AI in financial reporting, accentuating the importance of transparent, fair, ethical and controlled methods for incorporating this innovation. Addressing ethical issues, closing regulatory gaps and educating companies, investors, analysts and society at large about AI's impact, can help maximize its potential to improve financial transparency and integrity. Future studies need to further investigate these aspects, ensuring that introducing AI into a field as important as finance positively impacts the overall financial community and society as a whole.

8.2 Conclusion

Concluding this academic paper, its last section will end by going through the highlights of this novel research, conducted over the course of the academic year 2023-2024. This study began with the premise of exploring the transformative impact of artificial intelligence (AI) on financial reporting practices within medium to large, listed companies in the Netherlands. The objective was to understand how AI tools, used by investors and analysts to assess financial reports (i.e. annual/quarterly reports, etc.), influence the nature and amount of financial information reported by these companies. This research also aimed to investigate the strategies and adaptations employed by these companies, in response to the above-mentioned changes in their environment.

With the help of an extensive, self-crafted survey, the study sought to gather the experiences, viewpoints and thoughts of financial managers, accountants, and other industry professionals involved in financial reporting practices. This exploratory research method was selected for its ability to collect in-depth, qualitative information while guaranteeing anonymity, thereby encouraging honest responses from the participants on this delicate subject. Moreover, the survey was carefully planned to cover important areas of AI incorporation, such as awareness of its integration on the side of the financial markets, potential risks and challenges, response strategies and precautionary actions.

The results showed a complex situation, where AI's incorporation in financial analysis and decision-making boosts efficiency and accuracy, while also being the reason for notable concerns. Artificial intelligence has allowed for more rapid and advanced analysis of financial data, leading to improved investment decision-making and increased market efficiency. Conversely, the increased dependence on AI-generated results among investors has brought about new dangers, such as potential prejudices and a diminished focus on conventional financial evaluation and human oversight. This duality highlights the important, delicate and intricate nature of AI's involvement in financial markets.

To address these difficulties, companies are preparing to implement various tactics to protect the accuracy of their financial statements, their reputation and their chances of quickly raising external capital when needed. This involves creating more detailed financial statements to prevent AI algorithms from misinterpreting them, educating staff on how to utilise AI, fostering transparent communication among financial team members and stakeholders, and establishing internal controls to reduce risks linked to algorithmic analysis. The information collected demonstrates the significance of maintaining a balanced strategy by using AI for its advantages, while also ensuring ongoing human supervision to tackle its shortcomings.

The broader implications discussed, including ethical, legal, and societal issues, further accentuate the complexity of integrating AI into financial analysis and investment-decision making, as well as financial reporting. Ethical concerns about fairness, accountability, and transparency must be addressed to ensure that AI benefits all stakeholders equitably (Morley et al., 2021). Legal frameworks need to evolve to provide clear standards for AI usage in finance, ensuring responsible and ethical applications. And societal impacts, particularly on employment and skill requirements, necessitate proactive measures to support workforce adaptation and mitigate potential inequalities.

Aside from these implications, the research also surfaced several key themes for future exploration. For instance, there is a clear need for ongoing investigation into the development of regulatory frameworks, that can ensure ethical and responsible use of AI in financial markets. Furthermore, understanding the long-term implications of algorithms on financial reporting and analysis, as well as geographic differences in the effects that this tool has on companies, financial markets and society as a whole, remain areas open for further study.

In conclusion, this paper has provided a comprehensive overview of the current state of AI integration in investment decision-making and the corresponding reactions from companies within the Netherlands. It bridges the initial exploration of AI’s impact on financial reporting practices with practical recommendations for future research, thereby contributing valuable insights to both academic discourse and industry practices. As AI continues to evolve, its influence on financial reporting and investment practices will undoubtedly grow, requiring continued vigilance and adaptation from all market participants.

This study also serves as a foundational step in understanding and navigating this dynamic landscape, illustrating the importance of addressing the ethical, legal, and societal challenges that accompany technological advancements in finance. It supports the idea that harnessing AI's positive potential depends on responsibly adopting it with strong ethical principles and control mechanisms. That way, stakeholders could improve market efficiency and transparency, leading to a more balanced and fair financial system. So, it is essential for computer scientists, ethicists, policymakers, and financial practitioners to constantly communicate and work together across disciplines, in order to tackle the ethical and practical issues raised by AI. This approach would not just maximise the advantages of this intelligent tool, but also ensure that it stays in line with societal values, thus promoting a more inclusive and equitable financial environment.

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