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Artificial vs Human Intelligence

A qualitative study on how generative AI is impacting sell-side analysts

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Abstract

This thesis investigates how the current implementation of generative AI tools is impacting the role of the sell-side analyst. To acquire the relevant data, this study draws on ten in-depth interviews with both sell-side analysts and AI specialists. Using the theory of intertwined boundary work by Faulconbridge et al. (2023), this study showcases how generative AI tools are currently utilized by sell-side analysts as a starting point for initial, time-consuming tasks. Furthermore, this study demonstrates how the generative AI has led to four of Faulconbridge et al.'s (2023) modes of boundary work: *defending, creating, negotiating* and *coalescing*. Finally, this study further discusses two implications of these findings: (i) how the sell-side analysts' role as a financial intermediary changes and (ii) how they interplay with previously researched phenomena to impact the competitive dynamics of the sell-side analyst.

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Keywords: Sell-side analysts, generative AI, financial analysis, boundary work

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1. Introduction

1.1 Background

Capital markets prove an important role to facilitate trade among counterparties. One of the most crucial pillars of the functioning of these markets are the institutions and participants who ensure that capital is efficiently allocated and that information flows between investors and firms (Bradshaw et al., 2017). In the review paper by Kothari (2001), it is stated that one of the important factors of capital market research is the research on financial analysts. Among these financial analysts, sell-side analysts play an important role. Inevitably, the role that sell-side analysts play in capital markets has become a well-researched subject. Their tasks, which include forecasting (Ramnath et al., 2008; Brown et al. 2015; Whitehouse, 2017), communicating with different parties (Soltes, 2014), as well as gathering and analyzing data in order to make recommendations regarding different investment opportunities (Imam and Spence, 2016; Kuperman et al., 2003) may give the illusion that their role is stagnant and reduced to merely providing a financial analysis.

However, in reality, there are several elements which impact the sell-side analysts, making it difficult to define the role that they play. These include high competition (e.g. Barker, 1998; Graaf, 2023) and technological developments in financial accounting (Kurljusic and Karger, 2023). However, current literature does not, to the best of our knowledge, consider a modern innovation that has significant impact on sell-side analysts, namely the implementation of generative AI. Generative AI tools such as ChatGPT have changed the dynamics of several industries (Chen et al., 2023), including financial markets and thereby sell-side analysts. Given the fact that the interest of generative AI within financial analysis has recently surged, current literature has not had time to research how it impacts sell-side analysts.

1.2 Objective

Hence, in this study, our objective is to understand how the recent explosion and implementation of generative AI tools are impacting sell-side analysts. Thus, our research question is: *How is the implementation of generative AI in financial analysis impacting sell-side analysts?*

To answer this question, we have conducted a qualitative study, featuring semi-structured interviews with seven sell-side analysts and three AI specialists.

1.3 Contributions

We contribute to existing literature by displaying how sell-side analysts are impacted by the implementation of generative AI tools. Our empirics reveal that generative AI tools streamline certain tasks of the sell-side analyst. More specifically, they are used as a starting point for time-consuming tasks. This allows the analysts to e.g. more easily find peers, formulate texts and summarize data. Thus, the generative AI tools are mostly utilized in the information collection process and other initial tasks. However, when it comes to analyzing and interpreting this information, the generative AI tools are less efficient, meaning that the sell-side analysts have to rely on their own judgment and knowledge.

Furthermore, through the framework of intertwined boundary work presented by Faulconbridge et al. (2023), we find that the implementation of generative AI *creates* a boundary which separates those who use generative AI tools in their analysis from those who do not. To cross this boundary and venture into the realm of the superior analysts who employ generative AI tools, they *negotiate* with AI specialists in order to get the knowledge required to effectively use these tools. Furthermore, even without the help of AI specialists, our empirics show that sell-side analysts themselves start to conduct more technological activities. Consequently, their traditional, financial analysis tasks *coalesce* with their new technological activities, showcasing how the analysts themselves are becoming more knowledgeable within technology. However, we also find that the disruptive effect of generative AI causes sell-side analysts to downplay the abilities of the generative AI tools, for fear that they could be replaced or outcompeted by the tools or amateur investors who use these tools.

2. Domain and Method Theory

2.1 Literature Review

2.1.1 Financial Analysts

2.1.1.1 Who are financial analysts?

Financial analysts play an important role in capital markets (Fogarty and Rogers, 2005), but who exactly are they? The definition of financial analysts and the role they play is often difficult to define. According to Easley et al. (1998, p. 175), there are not many issues within capital markets that are more puzzling.

One of the most important roles of financial analysts is that they are “both mechanisms of information efficiency and as providers of benchmarks for consensus valuation” (Barker, 1998, p. 3). The global financial markets are influenced by many factors, and analysts help guide investors through these different types of markets (Whitehouse, 2017). They do this by responding quickly to relevant news (Barker, 1998) and providing investors with the information they need to make informed decisions (Moyer et al., 1989; Kuperman et al., 2003). In this sense, financial analysts act as important financial intermediaries (e.g. Schipper, 1991; Bradshaw, 2011; Bradshaw, 2009)

More precisely, by collecting macro- and microeconomic data as well as firm fundamentals (Whitehouse, 2017), financial analysts primarily provide investors with contextual information about a firm’s current situation and can thus be seen as providing valuation benchmarks (Barker, 1998; Hägglund, 2000; Imam and Spence, 2016; Spence et al., 2019). According to Barker (1998), analysts provide value as an information service with information advice for fund managers, rather than specific recommendations, forecasts, or channels of public domain information.

2.1.1.2 Buy-side vs Sell-Side Analysts

As of today, one can divide financial analysts into two main categories: buy-side analysts and sell-side analysts. Sell-side analysts tend to be employed by brokerage firms. Often specializing in a few particular industries (Fogarty and Rogers, 2005), they aim to provide price targets, generate earnings forecasts and make research recommendations whether to buy, sell or hold assets in a public setting (Imam and Spence, 2016; Kuperman et al., 2003). These would then be available to investors through various sources of information (Imam and Spence, 2016). The reports that they write should not just be informative, but also sell an “investment idea” to the investors reading them (Whitehouse, 2017).

Buy-side analysts, on the other hand, tend to work with fund management firms (Imam and Spence, 2016) as well as insurance companies and banks (Kuperman et al., 2003). Although they, like sell-side analysts, create reports and recommendations of e.g. new investment opportunities, these are more brief (Schipper, 1991). Moreover, as opposed to sell-side analysts, these reports are not written for the public (Fogarty and Rogers, 2005). The investment recommendations or decisions that the buy-side analysts make are done on behalf of their clients (Kuperman et al. 2003). In some cases, the buy-side analyst uses the information from sell-side analysts as support for their investment decisions (Schipper, 1991), proving a possibility for greater coverage of firms compared to sell-side analysts (Whitehouse, 2017). As argued by Schipper (1991), the tasks of the sell- and buy-side analysts are quite similar, although their incentives could differ considering their different employers.

The relationship between sell-side analysts and buy-side analysts is important. As buy-side analysts tend to cover more sectors and firms, they usually do not have the time for a deeper technical analysis of each firm they are covering, including perusing accounting information. Here, sell-side analysts have an opportunity to assist buy-side analysts in this field, while providing “technical capital” (Imam and Spence, 2016). This refers to a technical analysis that displays that a sell-side analyst has a greater technical understanding and knowledge of the valuation drivers of the firm they are covering.

2.1.2 The Sell-Side Analyst

Due to their “prominent role in analyzing, interpreting, and disseminating information to capital market participants” (p. 2), sell-side analysts are often of significant interest to academic researchers (Brown et al., 2015).

2.1.2.1 Acquiring industry knowledge

The sell-side analyst’s forecasts, estimates and recommendations regarding different investment opportunities are summarized in in-depth reports (Whitehouse, 2017). The creation of these reports is incredibly time-consuming. This is because the analyst needs to acquire extensive knowledge in order to do this, which requires a lot of research. They have to for example read companies’ filings for the stock exchange, have regular meetings with the company’s management, analyze its peers and familiarize themselves with the sectors and industries in which the companies operate. Because of this, a sell-side analyst will ideally not cover any more than 15 companies in two to three industries (Brown et al., 2015). Thus, they generally become experts in certain fields. Essentially, if they were to cover more industries or companies, there could be a risk that the quality of their reports would go down. Also, sell-side analysts are compensated for their industry knowledge that they provide to their institutional investors (Brown et al., 2015), showcasing the importance of this aspect of their work.

2.1.2.2 The importance of forecasting

To produce their reports and perform their other duties, sell-side analysts need to dedicate a considerable portion of their work to forecasting. Some of the different forms of forecasting conducted by financial analysts are earnings forecasting, target price forecasting and stock price recommendations (Ramnath et al., 2008). Previous accounting literature has tried to understand how financial analysts' forecasts are both derived and how they affect financial markets (see Schipper, 1991; Brown, 1993; Lang and Lundholm, 1996).

Among some of these literatures, Brown et al. (2015) suggests that industry knowledge is one of the most important inputs for sell-side analysts' in forecast models and stock recommendations. Furthermore, this knowledge is also valuable to their buy-side clients and is an important determinant of the sell-side analysts' compensation. In contrast, three things that are not as useful for earnings forecasts are: (1) recent stock price performance, (2) analysts' own stock recommendation and (3) other analysts' earnings forecasts.

However, although forecasting is important for the stock recommendations of financial analysts (see Brown et al. 2015), precision is not of considerate value for the clients. For example, Imam and Spence (2016) suggests that buy-side analysts do not find great value in forecasting itself. This is because the knowledge of an industry or sector is of greater value than forecasting skills, which would be inaccurate anyway given the uncertain nature of market assumptions and the lack of reliable information sources. Rather, forecasting is an opportunity for sell-side analysts to show their "technical capital" (Imam and Spence, 2016) towards buy-side analysts.

2.1.2.3 Communication as a contingent factor on the success of a sell-side analyst

Communication with different parties is vital in order to acquire the extensive knowledge required for their forecasts, stock recommendations, etc. For example, Soltes (2014) says that communication with management is an incredibly valuable source of information for sell-side analysts. Sell-side analysts are often in direct contact with the CEO or CFO of the companies they follow, especially during earning releases, which is when a majority (43%) of these meetings take place (Soltes, 2014). All in all, this relationship is an even more important input to their forecasts and stock recommendations than primary research, recent earnings performance, and 10-K/Q reports (Brown et al., 2015). However, it's not just management. To become a successful analyst, you have to build relationships with several types of people, including suppliers, key customers and government officials (Fogarty and Rogers, 2005).

Moreover, Barker (1998) argues that raw information from a company itself is of greater value compared to when it has been processed by analysts. This is because information from an analyst is inflicted based on a commission-based relationship (Barker, 1998, Schipper, 1991). At the same time, the information generated by analysts still plays an important role in the market for information (Barker, 1998). For example, the analyst community helps investors by having a consensus expectation of the market (Barker, 1998; Imam and Spence, 2016), such as advising clients in the midst of new accounting information, e.g. during reporting periods (Graaf, 2023). Thus, the analysis of sell-side analysts is not governed by an accuracy of accounting information as often believed, but rather by guiding the meaning of accounting information (Beunza and Garud, 2007; Vollmer et al., 2009).

2.1.2.4 Competition among sell-side analysts and how it is impacted by costs, media, criticism and regulation

Sell-side analysts have always been prone to high competition (e.g. Barker, 1998; Graaf, 2023), and there are plenty of driving forces and phenomena which impact this competitive landscape.

One of the driving forces for increased competition among sell-side analysts is the cost of sell-side analysts. Employers to these analysts, such as brokerages and investment banks, are faced with extremely high costs. For example, historically, it was seen as common for financial analysts to earn between 300,000-600,000 USD (Dorfman, 1996). However, despite these high salaries and bonuses, the actual income that is directly derived from the work of these sell-side analysts is almost non-existent (Whitehouse, 2017).

All the while, the infrastructure that is required in order for the analysts to make their recommendations, which was already high, has further increased. For example, as regulations have become more strict, more specialized staff is required to make sure that the analysts adhere to them. Overall, this has made it difficult to make huge profits from anything except investment banking deals. It has also meant that several financial analysts have been laid off in order to save costs, meaning that the analysts who are left have had to do more work to compensate. This has led to analysts having to cover for example 25 companies, rather than the regular 15. (Whitehouse, 2017)

Furthermore, the development of media and increased exposure has also made analysts more comparable to each other, thereby also impacting the competition between them. In order to avoid attention, some analysts seek to belong to the “herd”. However, other analysts utilize the media to stick out from the crowd and lead the herd (Cote and Goodstein, 1999). Some even reach the point where they reach celebrity-like status, consequently allowing them to receive much higher compensation (Fogarty and Rogers, 2005).

Moreover, sell-side analysts feel pressure outwards from the public, as there is a significant amount of criticism against the notion that analysts are experts. There is for example research suggesting that they can greatly affect the behavior of investors (Booker and Krishnan, 2000) and influence share prices (Schlienkamp, 2002). Furthermore, there is also research suggesting that sell-side analysts tend to create favorable reports with more optimistic earnings forecasts, especially if they are investment-banking analysts (Hirst, 1995: Lin and McNichols, 1998), and that they can prioritize their own relationships ahead of their objectivity (Schipper, 1991: Brown et al. 2015).

Regulations have also impacted the competition between sell-side analysts. An example was the implementation of Regulation Fair Disclosure (Reg FD). Which made it more difficult for analysts to gain an advantage on their peers by having private conversations with management (Soltes, 2014). Another example was the implementation of MiFID-II, which led to a transformation of how analysts were compensated for their research, and a more unforgiving market. Sell side analysts who mostly sell research would thus not earn as much money (Armstrong, 2018). Thus, the value of private information has been considered as important for the competitiveness of the sell-side analyst (Imam and Spence, 2016; Holland, 1998). At the same time, Graaf (2023) argues that private information is less central than as previously assumed. More specifically, Graaf (2023) found that private information is not considered as valuable as thought because clients were perceived as having greater access to the private information than sell-side analysts. Rather, the sell-side analyst is not as dependent on secret information on the market, but rather “sorting, interpreting, and distributing information openly in the public space” (Graaf, 2023, p.162)

2.1.2.5 The impact of technology on sell-side analysts

Another element which has greatly impacted sell-side analysts is the development of technology. Information technology and accounting have always been related, and this relationship has gradually been taken for granted to a point where accounting is not possible without information technology (Granlund and Mouritsen, 2003), and the same can be said for sell-side analysts. New advancements and innovations have constantly changed the dynamic landscape of the sell-side analysts and the industry in which they operate.

Accounting has always been subject to change and has affected sell-side analysts in multiple ways. However, accounting has never developed as fast as it currently does, which is correlated with digital transformation (Kurljusic and Karger, 2023).

There are several examples of technological advancements that impact financial information processing. For example, the development of computerized systems made it easier to track and record financial transactions, as well as quickly present these into financial reports (Ghasemi et al., 2011). Another example is the integration of spread-sheet tools that provided further support and served as the key digitalization advancement within accounting (Granlund and Mouritsen, 2003). Then, the usage of the world wide web and integrated information systems proved to be the second digital advancement within accounting (Porter and Heppelmann, 2015).

The latest part of these technological developments which have impacted financial information processing are some areas within artificial intelligence (AI). Although the origins of AI can be traced back decades ago, there is a consensus of the paramount importance featured nowadays by intelligent machines, as they are now becoming so sophisticated that almost no human intervention is required for their design and usage (Barredo Arrieta et al., 2020). Within finance, usages of AI are widespread and range from forecasting future costs (Kurljusic and Karger, 2023; Boussabaine and Kaka, 1998; Karaca et al., 2020), analyzing over-priced versus under-priced stocks (Creamer and Freund, 2010) and analyzing which financial metrics are the main drivers of wealth creation using AI techniques (Barnes and Lee, 2007). At the same time, this poses potential challenges for humans when working with machines and algorithms (Burns and Igou, 2019). An example of such a challenge is the concept of algorithm aversion, where information produced from a human source is often more relied upon compared to information from a computer source (Commerford et al. 2021; Önkal et al. 2009).

Although these matters have been raised by previous research, none of them, to our knowledge, have researched the implications specifically for sell-side analysts. Furthermore, these considerations are becoming more prominent with one of the most recent developments of AI: generative AI.

2.1.3 Gap and contribution

Thus, this poses the question of how the implementation of generative AI will impact the role of the sell-side analysts. All in all, research on sell-side analysts is well-documented. However, to the best of our knowledge, given that firms are only just starting to implement generative AI in financial analysis, research on how this impacts sell-side analysts is scarce. We thus aim to contribute to previous research by answering the research question: *How does the implementation of generative AI in financial analysis impact sell-side analysts?*

2.2 Theoretical Framework

The increased usage of generative AI has sparked different debates and research regarding how the future work of different professions will change. However, Faulconbridge et al. (2023) argue that there are only a few studies which detail AI's disruptive effects and how the implementation of AI causes professionals to defend their interests. Due to this, they have studied how professionals within accounting and law firms responded to the adoption of AI through *intertwined boundary work*. This is the "process by which professionals respond to disruptions and protect interests and resources by engaging in multiple interdependent modes of boundary work" (Faulconbridge et al. 2023, p. 1). Furthermore, Faulconbridge (2023)'s framework is adapted from the framework of Langley et al. (2019)'s review paper. Thus, the types of boundary work that Faulconbridge et al. (2023) studies originate from Langley et al. (2019). However, unlike Langley et al. (2019), whose study on boundary work consists of looking at the individual boundaries separately, Faulconbridge et al. (2023) also studies the interactions and interdependencies between different boundaries as they change due to disruption. In line with this, we find the framework of Faulconbridge et al. (2023) to be an appropriate way of analyzing our empirical findings and answering our research question.

2.2.1 Boundaries

Previous research states that boundaries are utilized to maintain interests and resources (Bucher et al., 2016; Muzio et al., 2013; Noordegraaf, 2020). Boundaries can be seen as "social constructions that create sites of differences" (Faulconbridge et al., 2023, p.2; Abbott, 1995, p.862) which people use to distinguish themselves from one another. In response to disruption, old boundaries are remade and/or new ones are created in order to maintain distinctions between different groups, and protect interests and resources (Bos-de Vos et al., 2019; Bucher et al., 2016; Quick and Feldman, 2014; Zietsma and Lawrence, 2010).

2.2.2 Ties

Faulconbridge et al. (2023) show that intertwined boundary work arises from two different kinds of ties: *opportunity ties* and *necessity ties*. Opportunity ties refer to when "one mode of boundary work creates an *opportunity* for other modes that generate additional benefits for the group in question*"* (Faulconbrige et al., 2023, p. 3). In contrast, necessity ties refer to when "one mode of boundary work *necessitates* other modes because of ripple effects that make the success of the first mode contingent on the enactment of other modes" (Faulconbridge et al., 2023, p. 3).

2.2.3 Different types of boundary work

According to Langley et al. (2019), there are three main types of boundary work: *competitive* boundary work, *collaborative* boundary work and *configurational* boundary work. Competitive boundary work includes how people distinguish themselves by constructing, defending or extending boundaries (Langley et al., 2019). Within this type, there are three different modes: *defending, contesting* and *creating.* Collaborative boundary work refers to how people realign boundaries by interacting with others (Langley et al., 2019). Within this type, one finds *negotiating, embodying* and *downplaying*. Finally, configurational boundary work "considers how people work from outside existing boundaries to design, organize, or rearrange the sets of boundaries influencing others" (Langley et al., 2019, p. 707). Within this type, the three modes are: *arranging, buffering* and *coalescing* (see table 1). All in all, the types of boundary work that are more relevant in our study are the competitive and collaborative types.

Table 1: Faulconbridge et al. (2023)'s definitions of types and modes of boundary work based on Langley (2019)

Types of boundary work (the goal and effects of boundary work)	*Competitive*	*Collaborative*	*Configurational*
Modes of boundary work (ways of performing boundary work)	**Defending** - established groups repairing a boundary that creates a dichotomy between insiders and outsiders **Contesting -** different groups struggle over a boundary in terms of who is an insider **Creating** - new groups creating a new boundary to legitimize their roles and protect their work	**Negotiating** - enabling collaboration by reforming boundaries **Embodying** - using people and their position to establish collaboration across boundaries **Downplaying** - purposefully ignoring boundaries to achieve collaboration	**Arranging** - Outside action to change the effects of boundaries on interactions to facilitate new activity **Buffering** - efforts to allow collaboration between groups from different social worlds with incompatible interests **Coalescing** - reshaping existing boundaries to allow activities to be brought together in a redefined space

Overall, Faulconbridge et al. (2023) states that boundaries "may be reproduced and strengthened through modes associated with competitive boundary work, but also simultaneously diluted through modes associated with collaborative boundary work and reorganized through modes associated with configurational work" (p. 5-6). Thus, during disruption, individuals will react in a way which will change the above-mentioned boundaries. Furthermore, unlike Langley et al. (2019), Faulconbridge et al (2023) also showcases how the connections between these different types and modes of boundaries are impacted as disruption occurs. Thus, they believe that these different modes of boundaries do not just coexist, but that they also 'intertwine'.

Faulconbridge et al. (2023) use this framework to study how accountants and lawyers in professional service firms (PSFs) are impacted by the implementation of AI. As mentioned by the authors, a limitation of this is that they cannot be sure how non-professionals, as well as professionals in other fields than those found strictly in accounting and law firms will react to different disruptions. Thus, to test the applicability of the authors' insights in other situations, we will take the framework and apply it in a new setting, by studying how the implementation of generative AI will impact sell-side analysts, and how they respond to this disruption.

3. Method

3.1 Research Design

As mentioned, the purpose of this report is to determine how the role of sell-side analysts will be affected by the implementation of generative AI. However, the degree of implementation of generative AI is rather unknown among sell-side analysts today, making it difficult to hypothesize about. Thus, since a quantitative approach usually requires a specific theory and initial hypotheses (Swanson and Holton, 2005) we believed that this type of study would not capture how the usage of how generative AI will affect sell-side analysts work. Therefore, we decided to study our research question through a qualitative study.

In practice, this has been done through in-depth, semi-structured interviews. This allows us to gain access to people's attitudes, experiences and thoughts (Pathank et al., 2013; Grossoehme, 2014), helping us answer our research question. Interviews are one of the most common methods for gathering qualitative data, with particularly semi-structured interviews often being the "sole data source for a qualitative research project" (DiCicco-Bloom and Crabtree, 2006, p. 315). Initially, we also planned to gather secondary data through document analysis. However, the unexpectedly high number of participants we managed to find meant that also including data from documents would have given us an overflow of data, forcing us to sacrifice quality for quantity. We thus concluded to only include data from the interviews.

Furthermore, these interviews were conducted at a cross-sectional level. As we wanted to gain a better understanding of how sell-side analysts as a whole group are impacted by generative AI, talking with different analysts at different firms gave us a better overall picture of how the industry is being impacted, rather than just one or two specific firms. Furthermore, because we suspected that the knowledge of generative AI would be limited among sell-side analysts, we also decided to interview specialists within AI. This would also provide greater contextual setting for the study, which helped us gain greater insights into how generative AI is impacting the industry.

We have approached the analysis of our study in a thematic manner. That is, we have through our interviews identified specific trends and attitudes regarding our research phenomena. A primary strength of this method is that it allows the user to "identify the motivations and concerns of accounting communicators" (Shoemaker, 1994, p. 1). Given the backgrounds of the participants in our interviews, approaching our research question through a thematic analysis has allowed us to gain access to the underlying thoughts and knowledge of our interviewees.

3.2 Data Collection

3.2.1 Semi-structured interviews

All of our data was gathered through semi-structured interviews. An overview of the interviews can be found in appendix 1.

3.2.2 Preparations

In order to establish contact for potential interviewees, we initially wanted to understand which firms utilize artificial intelligence and also employed sell-side analysts. The former was established using two approaches. The first approach was to initiate contact with employees who represented their companies at the Stockholm School of Economics's career fair, Handelsdagarna, and ask them about their profession and if they utilize artificial intelligence in part of their work at their workplace. The second approach was to search for firms that have publicly announced that they are using or developing generative artificial intelligence tools. The latter was based on a screening process in which we selected 50 financial companies. Within these firms, we aimed to find employees that either worked as sell-side analysts or closely worked with the development or implementation of artificial intelligence within the firm.

In terms of establishing the interviews, an initial email was sent to all the firms' employees or contact persons in either English or Swedish depending on the degree of internationality within the institution. This email summarized the aim of the study and asked for an initial meeting to elaborate on the study followed by a formal interview if interested. Out of the 50 firms that were contacted, the response rate was 15. Out of the 15 respondents, a total of 6 employees would accept our offer of having an initial interview. This initial interview lasted between 10-15 minutes in which we further explained our research question and also had the opportunity to ask them about their work. These interviews proved to be important for us to ensure that the interviewee was knowledgeable in the subject and could thus contribute to the study, and it also gave them the opportunity to address initial questions such as privacy matters and data collection. Furthermore, we believe that these were important as a first step to establish a proper relationship with the interviewees. The initial conversations were not recorded and could be considered as quite informal with a relaxed atmosphere. This ensured that the interviewees became comfortable with us, and the impression we got was that these conversations led to them becoming more interested in the subject.

In some cases, the employees we initially contacted redirected us to other colleagues, either during the first initial contact through email, or after an initial start-up interview. This was mostly due to the fact that the person we initially contacted was often unsure about the subject, and that they knew someone else at their company who they thought was better suited to answer our questions. Once the initial interview was finished, a formal interview was scheduled during March or April. In total, out of the 6 initial start up interviews, 2 did not want to proceed with another interview. This was mainly because they did not want to disclose any information regarding the subject. The rest of the interviews were held without an initial start-up interview before-hand because the interviewee did not have time for two conversations (both an initial start-up meeting and an actual interview). However, although not as effective, we still had email correspondence with these participants, which helped build a relationship prior to the interview.

Before the interview began, all interviewees were asked to sign a consent form that clarified their GDPR-rights, confidentiality, secured data storage, private data and that they could withdraw their consent at any time. Furthermore, all interviewees were asked if they wanted a preview of the interview guide (see appendix 2 and 3) before the interview began. Not sharing the interview guide beforehand could have ensured that the interviewees answered our questions more truthfully, as they would not have had time to prepare their answers. However, we believe that sharing it was pivotal in order to ensure that they were comfortable participating in a formal interview. Considering that artificial intelligence is a sensitive topic for many of the firms we interviewed, ensuring transparency and trust for the interviewees would hopefully allow them to speak about their work, and share greater insights during the interview. This was evident as many of the firms specifically asked if it was possible to see the questions before the interview. Furthermore, sending the questions before-hand helped some of the interviewees realize that there was someone else at their company better-suited to answer our questions.

3.2.3 Interview Guide

When creating the interview guide, the first step was to determine the content to be covered in approximately 45 minutes long interview. We initially started by writing several questions which were more focused on the person, including their position, organizational structure, communication among employees, etc. However, considering that many of our interviewees could be considered as prominent interviewees (see Maksymov et al., 2019), conducting the interview in a concise manner was important. Because of this, we came to the conclusion that these questions would not fit in a 45 minute time frame. Thus, the interview guide was revised with priority on generative AI. However, since we were planning to conduct semi-structured interviews, we made sure to keep the interview guide quite short and open, so that we would have time during the interviews to ask follow-up questions. Furthermore, given that we were interviewing both sell-side analysts and AI specialists, we created an interview guide for each group. These can be found in appendix 2 and 3.

3.2.4 Interviews

Out of the total ten interviewees (see appendix 1), seven were sell-side analysts or had previously worked in positions as sell-side analysts, and three were specialists in implementing generative AI in organizations. Out of these interviews, five were conducted online, at the request of the interviewees. Given the busy schedules of the analysts and the AI specialists, sensitivity of many of their operations, and different geographical locations, the convenience of having an online interview meant that we expected this before-hand. The other 5 interviews were conducted at the interviewees' offices. We found that this allowed us to get a better connection with the interviewees, and overall led to better discussions. All but two of the interviews were conducted by both of us together. Doing the interviews together proved an opportunity for more knowledge-sharing, as we were able to combine our different inputs and perspectives on the interviewees' responses, as well as help each other formulate our questions more clearly. Furthermore, although it would have been easier with regards to this study to conduct all of the interviews in English, we made sure to carry them out in the interviewee's native language. This was to decrease the risk of language barriers and limiting the interviewees' ability to express themselves, which would have hindered us from properly extracting the perspectives and thoughts of the interviewees.

Each interview started with a quick introduction, where we introduced ourselves, what our study was about and what kinds of questions we would be asking. Furthermore, we also reminded the interviewees about the documents regarding GDPR that they signed, and what they actually meant. We asked for permission to record each interviewee and made sure that they were comfortable by letting them know that they could stop the recording whenever they wanted. During the interviews, we made sure to follow our interview guide. Although it could have been more interesting to let the conversations we had developed completely on their own, this would not have allowed us to compare the different interviews as well, and also pose the risk of passing the time limit with the interviewee. Because of this, we made sure to follow the interview guide. In this regard, it was helpful to have both of us doing the interview together, because if one of us strayed too far from the interview guide, the other could bring the topic of conversation back on course. Furthermore, the interview guide was still written as if the interview would be semi-structured. This allowed us to preserve a degree of comparability between the interviews, while still being able to speak "freely" during each interview. This enabled us to build a deeper relationship with the interviewees and acquire data which we otherwise probably would not have.

3.3 Data Analysis

The data analysis segment was conducted continuously as we conducted our interviews. After each conversation, we immediately sat down together and discussed the interviews. We wrote down our thoughts and main take-aways, and then proceeded to transcribe the interviews. Transcribing was done by one person right after the discussion, and then proof-read by the other and vice versa. This was in order to ensure the correctness of the transcription. When dictating, we initially transcribed every word that the interviewee said, and then summarized them by structuring them into different sections, each section representing an answer to a question we asked. We then summarized the findings from each section, making them easier to compare with the findings from other interviewees.

In terms of coding our responses, we began separating the standardized responses, such as how many years experience each interviewee had in their field, or what their daily tasks were. The most relevant data here is summarized in appendix 1. Standardized questions related to generative AI proved as a proxy of the interviewee's AI-knowledge. Here, we made an assessment of the interviewees' AI knowledge based on their own opinion regarding their AI knowledge, as well as how they responded to our AI-related questions.

The non-standardized responses were color-coded based on the framework presented by Faulconbridge et al. (2023), where each mode of boundary represented a different color. For example, if a particular response was connected to the defending mode of boundary work, this would be coded in a specific color.

4. Empirical Findings and Analysis

In this section, we present the relevant findings of this study and analyze them using the theoretical framework from Faulconbridge et al. (2023) to conclude the impact generative AI will have on the sell-side analyst.

4.1 General Findings

Firstly, our study finds that all seven sell-side analysts are using generative AI in some part of their work. Typically, it is used for inspiration and provides assistance for time-consuming tasks such as finding peers, formulating texts, and summarizing data and texts. All sell-side analysts report that generative AI tends to be very efficient at performing these tasks, although they do not believe that all of the data provided by the generative AI system is accurate. Therefore, the sell-side analysts must peruse the generative AI's output and only select the relevant information, which is then analyzed in a separate stage.

At the same time, our study suggests that sell-side analysts do not utilize generative AI for all tasks. For example, none of the sell-side analysts report that they use generative AI for analyzing companies or sensitive information. This is typically justified by some form of aversion to using generative AI, such as believing that generative AI does not provide accurate information, or distrusting it to handle private information of a company. Overall, sell-side analysts are using generative AI, but still remain hesitant to use generative AI for all types of tasks.

Secondly, our study shows signs that generative AI has led to an increased collaboration between sell-side analysts and specialists within technology and generative AI. A common theme among both generative AI specialists and sell-side analysts is the surge of interest in the field of generative AI since approximately 2021, when generative AI became more easily available for the public through systems like ChatGPT. This has sparked an interest for the potential of generative AI and how it can favor e.g. sell-side analysts. This has been shown by internal initiatives like having generative AI pilot studies with sell-side analysts, or having some of the sell-side analysts being part of an internal AI committee. These initiatives have increased the collaboration between sell-side analysts and those working with the implementation of generative AI as either consultants or internal employees. At the same time, all of the sell-side analysts report that their generative AI knowledge is rather limited. For example, they report that they do not know how or what information the generative AI selects and that much of it is seen as a black box. Overall, even though sell-side analysts are beginning to collaborate more with generative AI specialists, their generative AI knowledge remains limited.

4.2 Findings through the lens of boundary work

This section consists of a further analysis of our general findings (section 4.1) based on the theoretical framework of *intertwined boundary work* by Faulconbridge et al. (2023).

4.2.1 Defending - *downplaying the abilities of the generative AI tools to protect their jobs*

The impact of generative AI on the tasks of the sell-side analyst has led to a competitive type of boundary work. More specifically, the disruptive effect of generative AI has led to *defending* among the sell-side analysts.

First of all, a large part of the sell-side analyst's task is to find comparable firms based on factors like size and sector when valuing a company:

> *You need peer companies in almost all valuation projects. If you want to evaluate company A, you will need to find, preferably, listed companies that are comparable to company A.* (Analyst 1)

To do this, sell-side analysts have started to use generative AI. In the process of finding peers, all seven of the sell-side analysts express that they are using generative AI to find comparable firms, as mentioned in 4.1. More specifically, they ask the generative AI to identify and list potential comparable firms for a specific company. However, the sell-side analysts then only select companies that they deem as relevant for further analysis. This decision is based on the analysts own experience and judgment:

If you would Google comparable firms, you would barely find anything. Or you can screen in tools like Bloomberg, Capital IQ, Factset or search for keywords or standard industry classification, and then evaluate which [companies] fit well. Then, you can think which firms are relevant and fit well [in comparison to company]. The strength of using AI, for example, is to receive input regarding which firms are comparable and who sells similar products on these markets, or the AI might find a market report which lists competitors. We can then use that as inspiration and take that to the next level using our tools to see if we agree with that [recommendation of AI]. Perhaps we find a great peer, to which we can download stock analysis reports for the firm and see their peers. It is a great starting point. (Analyst 1)

The selected firms are then further processed by the analyst by manually extracting accounting data like EBITDA, but also relevant ratios and margins. This information is often extracted from other sources that are used in the firm, such as Bloomberg and Capital IQ. In essence, generative AI is considered as a tool used for inspiration to find comparable firms, of which only certain ones are selected.

Second of all, a large part of the sell-side analyst's tasks consists of extracting relevant information for their analysis. To do this, they read lengthy reports such as annual reports, sector-specific market reports or global macroeconomic trend reports. However, this is a time-consuming task. Thus, in order to save time, sell-side analysts use generative AI to help them summarize these reports and extract the relevant data, as mentioned in 4.1. Interestingly, compared to other tasks, analysts have more faith in their generative AI tools when it comes to extracting and summarizing data. Part of the reason comes from the fact that when summarizing data, the analyst can control the original input source from which the generative AI bases its output on. However, despite this, analysts still emphasize the limitations of using generative AI to summarize data. Similar to finding relevant peers, sell-side analysts use generative AI as an initial method to extract common information, such as size and industry, which gives them a brief overview of the company they are analyzing. However, if they want to reach a deeper understanding of a company or industry and acquire the level of expertise that is usually required in their analysis, they need to gather information manually as well.

I often have to read long reports in order to get the right information, and I often don't know exactly where the information I want is located. So, in these situations, I use AI

> *to help me summarize these texts, and this helps me find the information more quickly.* (Analyst 4)

Third of all, as mentioned in 4.1, a large task of the sell-side analyst is to present relevant information in text format, including briefings, information sheets and e-mails. These are then distributed internally within the firm, but also externally to clients. Here, generative AI helps to create and structure texts as well as proofread texts:

> *A large part of [my AI usage] is writing texts. For example, if you are writing and do not really know how to formulate yourself, you can put in your text and then you get suggestions.* (Analyst 5)

However, similar to identifying peers and extracting and summarizing information, sell-side analysts only use generative AI as an initial tool to formulate brief sentences or parts of texts, and then continue to refine the output from the generative AI based on their own judgment and experience. More specifically, the sell-side analyst must ensure that the text is coherent and is up to standard to be distributed to clients and colleagues:

> *Partly it is a great tool to formulate mails, and help with structuring sentences. Although, we do not use a full page as input, and ask the AI to rewrite the text. Rather, you write that there is a specific part of the text that lacks clarity, and asks the AI to enhance that sentence. Then, we can take the suggestions and perhaps change a few words.* (Analyst 2)

Thus, sell-side analysts use their own judgment to decide what is relevant and use their own style of writing, meaning that they can act as a gatekeeper to decide the output that is distributed to clients and colleagues.

Overall, a common theme among these three findings is that although sell-side analysts describe how generative AI is a beneficial tool, they clearly accentuate what their generative AI tools cannot do. Similar to what was found among accountants and lawyers by Faulconbridge et al. (2023), the sell-side analysts' reaction and thoughts regarding the capabilities of generative AI can thus be seen as a competitive type of boundary work in the form of *defending.*

4.2.1.1 - Distinguishing between generative AI and the sell-side analyst

Sell-side analysts defend their position by restricting what type of tasks the generative AI tool does and can do. Sell-side analysts are an established group of professionals characterized by being one of the few professional groups able to conduct an accurate financial analysis. This seclusion benefits the analysts, as it leads people to regard them as experts, which helps justify their high status. However, the growing usage of generative AI has started to raise a concern that more tasks of the sell-side analyst could be replaced by artificial intelligence. As more of these concerns populate the industry, the boundary which separates what the sell-side analysts can do and what the generative AI can do fades. This causes them to lose their title as experts and run the risk of having much of their work substituted by generative AI systems. However, by restricting what the generative AI can do, the sell-side analysts work towards reestablishing this boundary. More specifically, the sell-side analysts use their judgment and expertise to select and voice which tasks the generative AI can do, and which tasks it is not sufficient for. Similar to accountants and lawyers in the study by Faulconbridge et al. (2023), sell-side analysts restate claims, since they reiterate that generative AI cannot fulfill the whole process of tasks that the sell-side analysts normally do on their own. By doing this, they have the power to create a boundary that defines the difference between tasks which are adequate for the generative AI tool and tasks that require the sell-side analyst's expertise.

What we typically see is that sell-side analysts create a processed-based dichotomy between (1) the initial, elementary part of a task, and (2) the more complicated, finalization of this task. In these two parts, generative AI is considered as an adequate tool for the former. For example, as mentioned earlier, when establishing peers for a valuation, the sell-side analyst uses generative AI as a starting point to get a list of potential comparable companies for "inspiration". However, they then express the limitation of the generative AI tool by explaining how it is unable to make the necessary judgments and face the same questions as the analyst does, and that they therefore have to use their own judgment and expertise.

Another example also mentioned earlier is text formatting. Here, the sell-side analyst expresses that they can use generative AI in the initial stage by producing a new text or improving an old one. However, the sell-side analyst differentiates itself from the generative AI by highlighting issues like hallucinations, or that the text it generates is in a format that is not custom for their clients or internally for their colleagues. Therefore, they have to use their own knowledge to shape the text in a more adequate way. Similarly, when they for example extract and summarize information, they use generative AI in the initial step when they need to quickly get access to easily obtained information and get a quick overview. However, when they later need to get a deeper understanding, they have to procure the information without these generative AI tools.

Thus, by highlighting the limitations of generative AI tools and elucidating their inferiority to the analysts themselves, the sell-side analyst defines and in a certain sense control what the generative AI cannot do. In other words, they convey that the generative AI cannot operate without the sell-side's expertise, which allows them to maintain the boundary that separates their expertise and capabilities from the generative AI tool's expertise and capabilities. This then helps them protect their job and extinguish notions that their tasks could be replaced by a generative AI tool.

4.2.1.2 - Distinguishing between amateur investors and sell-side analysts

Other than attempting to maintain the boundary between the capabilities of a generative AI and the actual analyst, sell-side analysts also try to uphold the boundary separating them from "regular", amateur investors. What has long separated sell-side analysts from these types of investors is the deep knowledge that the analysts possess. The knowledge required to conduct an accurate analysis has usually been difficult to acquire and restricted to those within the financial industries. Sell-side analysts have thus thrived in their own space where they are regarded as experts and superior to other amateur investors, which has constructed a "need" for the sell-side analyst. However, the implementation of easy-to-use generative AI tools such as ChatGPT has made it simpler for people to get access to information that is otherwise considered to be more difficult to obtain. For example, amateur investors can use generative AI as a starting point for knowing where to find relevant information, which is otherwise difficult to do without previous experience or knowledge. Generative AI has therefore blurred the boundary that has allowed sell-side analysts to maintain a degree of superiority compared to others. Thus, in order to repair this boundary and maintain the dichotomy between sell-side analysts and other amateur investors, analysts downplay the ability of generative AI tools to extract and analyze information, consequently conveying how only a sell-side analyst can truly perform these tasks.

4.2.2 Creating - *the creation of a boundary which distinguishes the superior group of sell-side analysts who utilize generative AI*

Although all seven of the sell-side analysts mention that generative AI cannot replace them, eight of our interviewees (including all three AI specialists) see the development of generative AI tools as a key factor to continue to be competitive in the industry, potentially explaining why all of them sell-side analysts have started to implement generative AI in their work.

Generative AI creates a new boundary because it poses the question regarding which analyst and firm will be an insider versus an outsider in the race of having generative AI capabilities. Here, the superior, insider group is the one with generative AI capabilities, while the inferior, outside group is the one without generative AI capabilities. This new boundary has created a possible race between firms to acquire the best generative AI capabilities. In this race, there is a fear of missing out on the potential of what generative AI can do for a company:

> *[...] Imagine if you are a bank and you see the other bank doing five decisions while you do one. That is how the hype happened actually, because everybody is now scared. Someone who even has, like, worse employees now with these technologies might overtake me if I'm not careful, so I also have to keep my eyes open. [...] when it comes to talent from schools, maybe the top three banks will pick up [the best talents] and the rest of the banks will get a lower tier of talent. But if those banks who are in the lower tier are smart to implement gen[erative] AI solutions with lower talent of colleagues, they might overtake the bank that has the top-tier talent, right? So that is why everybody says 'Ok, we cannot let someone have gen[erative] AI and we don't.' So that is where the demand for gen[erative] AI comes from now.* (AI specialist 1)

> *[...] There is a large anticipation in many organizations, including ours, that we need to get AI. I think no one wants to be the second one [to implement it] so everyone does it because they need to do it and should do it to remain modern. But I wonder if everyone knows what the use-case of it is in each case. I feel that it is similar for our case: you want to use it, but it is not clear what the use-case is. Perhaps the cost is higher than the benefit, for the moment at least.* (Analyst 7)

> *[...] I definitely think that in 20-25 years, it will become much more important that you have the best AI tools than that you use for example specifically use our company's services, but there is a clear step between now and then.* (Analyst 1)

Particularly, when a firm uses generative AI in their analysis, many of the sell-side analysts believe that the position of their firm strengthens. Indirectly, the position of the analysts who work at this firm are then also strengthened. One could therefore argue that generative AI creates a new boundary which distinguishes analysts who work with generative AI. It becomes important for sell-side analysts to work with generative AI and for them to work at a leading firm that uses the newest generative AI technology in their analysis. Similar to what Langley et al. (2019) argue, this gives sell-side analysts and the firms an opportunity to position themselves as more valuable and seek legitimacy from that. This ensures that they are included in the newly created superior group, which helps them to distinguish themselves in the already competitive environment that sell-side analysts find themselves in.

In total, generative AI appears to be a deciding, differentiating factor that creates a boundary which differentiates firms and analysts by creating a new group of analysts who are utilizing generative AI. Having the latest generative AI function can prove an opportunity for firms and analysts to position themselves as a preferable group in an already highly competitive group.

4.2.3 Negotiating - *increased collaboration between sell-side analysts and technology specialists*

In addition to *defending* and *creating*, we also found a collaborative type of boundary work in the form of *negotiating.*

The implementation of more generative AI tools has led to a reformation of certain boundaries within larger firms who have their own internal IT department and AI functions. More specifically, as mentioned in 4.1, the implementation of generative AI tools has led to new cooperation between sell-side analysts and AI experts who work within the tech departments. The reason behind this is that the competencies of the sell-side analysts (i.e. the group who will be using the generative AI tools) and the technology specialists (i.e. the group who integrates the tools) complement each other. Given that the AI specialists' knowledge of generative AI is greater than the sell-side analysts', the sell-side analysts are dependent on them to implement accurate tools which the sell-side analysts can benefit from. At the same time, the AI specialists are dependent on the feedback and cooperation of the sell-side analysts in order to ensure that they can get the most of the generative AI tools. The success of the generative AI tools is thus contingent on both groups. This dependency on one another has thus facilitated collaboration, which comes in the form of for example direct support and workshops:

> *So a big part of our job is to educate and inspire the organization… It can mean like having presentations, workshops, courses or by doing use cases… And by doing this, we first of all, inspire, educate and also help the organization grow in terms of writing, like finding right competence and also finding the right questions to ask because not everyone is an AI practitioner.* (AI specialist 3)

Furthermore, there is not just an increased collaboration between the sell-side analysts and the AI specialists within the same firms, but also between the sell-side analysts and external parties in the form of consultants who specialize in AI. Like the AI specialists within the firms, they also provide knowledge and help the sell-side analysts find new ways in which their work can benefit from using generative AI:

> *How it [the generative AI-tools] works in the background is something that most [of our customers] do not understand… so the overall technical knowledge is low… but they at least have to understand what kinds of opportunities and challenges it [the generative AI-tool] creates for their company.* (AI specialist 2)

Thus, the clear boundaries between analysts and technology specialists within firms are becoming less evident, as the two groups cooperate more. Similarly, as in the study of accountants and lawyers in professional service firms (PSFs) conducted by Faulconbridge et al. (2023), one could argue that technology specialists have been reclassified and accepted as co-operators who directly contribute to the success of the sell-side analysts. Therefore, the boundaries between these two groups have reformed by bridging. A similar parallel can be drawn between analysts and external consultants.

However, as mentioned earlier, this is something that we only see within large firms that have a separate IT department and in firms with enough resources to employ consultants. As smaller firms have less resources and tend to not have their own tech department with AI experts, there is a limited possibility for the analysts to collaborate more with these kinds of experts.

4.2.4 Coalescing - *the convergence of financial analysis tasks and technological tasks*

Finally, something that we see with analysts in both large and small firms is the configurational type of boundary work *coalescing.*

The hype train of generative AI and the increased implementation of different generative AI tools has led to a slight shift in the role of the sell-side analyst. As briefly mentioned in 4.1, this has led to a larger part of their tasks consisting of those who would normally be associated with an employee in an IT department. Analysts now do not just for example value companies, but also contribute to AI departments and try to find new ways of using generative AI tools to help make them more productive. For example, "[...] I personally use it [generative AI], even because I am in an AI committee where we have discussed the usage and so on." Analyst 1.

Moreover, we find this shift is not something merely forced onto the sell-side analysts by the AI specialists, but something that is also driven internally among the sell-side analysts: *"I think the cool part is at our firm, that the push [of implementing generative AI tools] is from both sides [analysts and AI specialists]"* AI specialist 3.

Furthermore, the desire to implement generative AI is also clear with sell-side analysts in smaller firms. In these types of firms, where AI specialists are missing, sell-side analysts have had to "learn by doing" themselves. This also shows that the above-mentioned shift in the role of the sell-side analyst is not caused by an external party directly forcing or encouraging them to use generative AI tools, but a change that is also driven by sell-side analysts themselves.

Thus, the increased implementation and hype of generative AI among sell-side analysts has reshaped an existing boundary which kept two activities, the *financial analysis activity* and the *technological activity*, separate. This change has allowed these two separate activities to come together in a redefined space, where sell-side analysts conduct both of these activities.

5. Discussion

Using the framework by Faulconbridge et al. (2023), we can draw four key conclusions. Firstly, sell-side analysts downplay the capabilities of generative AI in order to defend their position from amateur investors and generative AI tools. Secondly, sell-side analysts realize the potential of these tools, and thus strive to become an insider and part of the superior group who utilize generative AI. Thirdly, in order to reach this group, sell-side analysts collaborate more with AI specialists. Finally, this has also led to sell-side analysts taking on more technological tasks in their daily work.

In this section, we will discuss our findings further in two parts. Firstly, we will discuss how the use of generative AI will affect sell-side analysts' way of processing information, and how this will impact their role as financial intermediaries. Secondly, we will discuss how generative AI impacts the competitive landscape of the sell-side analyst, including a sub-contribution of how intertwined boundary change impacts competition.

5.1 Streamlining tasks and the sell-side analysts' role as financial intermediaries

In line with previous research (Brown et al., 2015; Whitehouse, 2017; Schipper 1991, Imam and Spence, 2016; Brown, 1993), our findings suggest that the role of the sell-side analysts is to collect, analyze and process significant amounts of information. Our findings show that this information is then provided to other financial actors, such as investors, which is in line with previous research (Schipper, 1991; Brown et al., 2015).

At the same time, our findings also contribute to previous research on how disruptive digital technology is used and impacts sell-side analysts by highlighting how specifically generative AI impacts sell-side analysts. Our study suggests that the actual interpretation of financial information by sell-side analysts remains similar to previous research (see Barker, 1998; Graaf, 2023; Benunza and Garud, 2007; Vollmer et al., 2009), although generative AI eases the process of collecting information.

On one hand, our data suggests that the quality of information processing hinges on the sell-side analyst utilizing their previous experience and judgment, while simply collecting information does not require the same expertise. One could argue that generative AI does, therefore, not alter the quality of the output that is provided to investors, because the sell-side analyst remains selective in terms of which information is chosen for further analysis. This would be similar to previous findings on how technological advancements such as the integrated information systems and spreadsheets impacts financial information processing

(Ghasemi et al., 2011; Granlund and Mouritsen, 2003). Furthermore, this also suggests that generative AI does not compromise the important role of how sell-side analysts are important intermediaries to process financial information (e.g. Barker, 1998; Schipper, 1991). Thus, our study displays that although disruptive technologies like generative AI have the ability to conduct much of the work done by sell-side analysts, thereby making them more efficient, the important role of sell-side analysts as financial intermediaries remains unchanged.

On the other hand, through the boundary framework of Faulconbridge et al. (2023), we found that the defending mode of boundary work played a large part in the sell-side analysts' response to generative AI. By downplaying the abilities of generative AI, one could conclude that sell-side analysts are using this mode of boundary work to defend their position as financial intermediaries. This would make generative AI appear as a tool, similar to the integrated information systems and spreadsheets (Ghasemi et al., 2011; Granlund and Mouritsen, 2003), rather than a disruptive technology that threatens the role of the sell-side analyst. Therefore, the question arises whether generative AI tools are actually incapable of conducting the work of the sell-side analyst, or if the limitations of generative AI are crafted by the sell-side analysts to defend their positions as financial intermediaries.

Moreover, our findings do question the future role of sell-side analysts as being an informative financial intermediary with generative AI. As mentioned, our study shows that sell-side analysts rely on their judgment when assessing the financial information provided by generative AI. However, this judgment, which relies on previous experience and knowledge, is built and acquired by manually doing the work which is now performed by the generative AI. In the case of up and coming, less experienced sell-side analysts, the question arises if they will be able to accumulate the same competencies that current, experienced sell-side analysts possess to make the necessary judgments when selecting and analyzing information. In essence, by utilizing generative AI, future sell-side analysts risk losing knowledge compared to sell-side analysts today.

This can be seen from two perspectives from previous literature. Firstly, the critique of the notion that sell-side analysts are experts (e.g. Booker and Krishnan, 2000; Hirst, 1995) could suddenly become more legitimate in the future if they do not possess the expertise and knowledge to analyze information. Paired with the fact that many sell-side analysts do not have extensive knowledge of how generative AI works, the risk of future sell-side analysts being efficient financial intermediaries and processing financial information is then threatened in capital markets. This would contradict with literature suggesting that sell-side analysts in fact are efficient financial intermediaries (Schipper, 1991; Imam and Spence, 2016; Bradshaw, 2011; Bradshaw, 2017).

Secondly, the risk of sell-side analysts not having enough knowledge about (i) generative AI and (ii) the role of the sell-side analyst's position in capital markets, further fuels the issue of sell-side analysts' tasks being viewed as a black box. Previous research (see Brown et al., 2015; Ramnath et al., 2008; Bradshaw, 2011) has called for and attempted to unbox the role of the sell-side analyst and gained further insights in their decision-making process. However, our study poses the suggestion that generative AI tools can erode the knowledge of sell-side analysts to the extent that their job becomes a black box for themselves, which possibly makes the quest to understand the role of sell-side analysts for researchers (see Ramnath et al., 2008; Bradshaw, 2011) more intricate than before. This puts greater emphasis on ensuring that sell-side analysts gain greater insights in how generative AI works.

In regards to this, the negotiating mode of boundary work found in our study, which enables the transfer of knowledge of generative AI from AI specialists to sell-side analysts, becomes important. By erasing the boundaries between sell-side analysts and AI specialists, large firms create an environment which fosters collaboration between the two, which facilitates this knowledge transfer. This is important as it can mitigate the future risk of sell-side analysts not understanding generative AI and viewing it as a black box. As such, the negotiating mode of boundary work will be an important factor to prevent the knowledge erosion of the sell-side analysts, and their tasks becoming a black box to research (Brown et al., 2015).

In total, our findings describe how the tasks of sell-side analysts are affected by the implementation of generative AI. Thus, we contribute by displaying how sell-side analysts are affected by the implementation of new digital technologies and how their tasks are changed through tools that make their work more efficient. Furthermore, our findings also contribute to the previous literature of sell-side analysts as being financial intermediaries by processing information to other financial parties, but in this case, in the midst of new digital tools that make their work more efficient. Finally, our study raises a potential issue of generative AI closing the black-box of the analytical process of sell-side analysts.

5.2 Competitive dynamics of the sell-side analysts

Consistent with prior studies (e.g. Barker, 1998; Graaf, 2023), we find that sell-side analysts experience high competition. Moreover, our findings also contribute to previous research on driving factors and phenomena that impacts the competitive landscape of the sell-side analyst (Dorfman, 1996; Whitehouse, 2017; Fogarty and Rogers, 2005; Booker and Krishnan, 2000; Schlienkamp, 2002; Hirst, 1995; Lin and McNichols, 1998; Schipper, 1991; Brown et al. 2015; Soltes, 2014; Armstrong, 2018, Imam and Spence, 2016; Holland, 1998), by showcasing how the implementation of generative AI interplays with these factors to change this competitive environment.

Firstly, the implementation of generative AI impacts the competitive landscape by affecting costs. As stated by Dorfman (1996) and Whitehouse (2017), the costs associated with employing sell-side analysts are extremely high, and this is one of the drivers of the high competition between the sell-side analysts. However, nuancing this, because generative AI is able to streamline the work of the sell-side analyst and make them more efficient, we believe that the costs of the firms employing these sell-side analysts could decrease. This could potentially relieve some of the sell-side analysts' pressure, as they would not have to work as much to justify their high costs. However, as stated by Whitehouse (2017), the phenomena of firms laying off financial analysts to save costs is not unusual. Extending this idea, we find that there is a risk that firms may see the implementation of generative AI as an opportunity to lay off sell-side analysts, since a sell-side analyst using generative AI can do more than what they could do prior to the implementation of generative AI. In other words, the firms can employ fewer sell-side analysts (thereby reducing costs), and still reach the same level of output.

Secondly, our study shows how the implementation of generative has led to the sell-side analysts potentially competing with not just each other, but also the actual generative AI tools, as well as amateur investors who utilize these tools. All in all, this puts pressure on the sell-side analysts and increases the competition for them. In response to this, we see how sell-side analysts defend their position by downplaying the abilities of the generative AI tools and simultaneously expressing how their own experience and expertise is needed to conduct an accurate financial analysis.

Thirdly, the implementation of generative AI impacts the criticism towards sell-side analysts. The pressure from researchers on sell-side analysts affects the degree of competition between sell-side analysts. On one hand, we broadly speculate that they can contradict previous literature which criticizes their expertise (Schlienkamp, 2002; Hirst, 1995; Lin and McNichols, 1998; Schipper, 1991). More specifically, we find that the implementation of generative AI tools could oppose these critiques, as the sell-side analysts would thus be relying more on a non-biased information source which does not have any other motives. On the other hand, our findings also show signs of increasing critique against sell-side analysts. As mentioned in 5.1, the implementation of generative AI can also undermine the expertise of the sell-side analysts, consequently supporting previous literature (Booker and Krishnan, 2000; Schlienkamp, 2002; Hirst, 1995; Lin and McNichols, 1998). When more generative AI tools are used and more of the spotlights end up on these tools, the question arises whether the sell-side analysts are still needed, or if the machine can do most of the tasks.

Altogether, our findings showcase the high degree of competition between sell-side analysts, and how the implementation of generative AI impacts this. Consequently, we contribute to previous research on the competitive landscape of the sell-side analyst, by nuancing how generative AI interplays with previously researched phenomena and drivers of the competitive environment. By showcasing the interaction between generative AI and the other phenomena, we highlight how the competitive environment of the sell-side analyst is changing.

5.2.1 Sub-contribution: Boundary work's impact on the competitive environment of the sell-side analysts

Overall, the high degree of competition as mentioned by Barker (1998) and Graaf (2023) means that sell-side analysts need to differentiate themselves if they want to be highly compensated. Extending this, our findings show that generative AI has allowed sell-side analysts to find new ways to differentiate themselves from others, thereby also impacting the competitive landscape. As we found through the lens of boundary work (Faulconbridge et al., 2023), generative AI has led to a *creating* mode of boundary work. More specifically, a new boundary which separates sell-side analysts who combine their own expertise and knowledge with the usage of generative AI tools is being created. This enables sell-side analysts to strengthen their position by working with generative AI tools and by working in a firm that uses the latest generative AI technology, thereby differentiating themselves. From the perspective of Cote and Goodstein (1999), there are two potential reasons for this. Sell-side analysts could (i) work with generative AI to become leaders of the herd, or (ii) work with generative AI because this has become the new norm, and they do not want to stick out as an inferior analyst. All in all, the desire to be in this superior group has created competition among firms to adopt generative AI tools, and a desire among sell-side analysts to work at a firm who use advanced generative AI-technology.

As mentioned earlier, sell-side analysts' desire to end up in this newly created group necessitated a deeper collaboration with AI specialists. The bridging of boundaries between these two groups has fostered new opportunities for knowledge sharing between them, leading to the *negotiating* mode of boundary work. Therefore, besides preventing a potential black box issue as mentioned in 5.1, this mode of boundary work has acted as a *necessity tie* for the *creation* of the new boundary which distinguishes the new, superior analysts.

Furthermore, the argument could be made that the *creating* mode of boundary emerged from not just a *necessity tie*, but also an *opportunity tie*. As mentioned earlier, generative AI has caused the role of the sell-side analyst to shift from conducting only financial analysis activities to also more technological activities through coalescing. This has given analysts the *opportunity* to redefine themselves and strengthen their position. Thus, *coalescing* has created the opportunity for *creating*, which in turn generates additional benefits for sell-side analysts by allowing them to navigate their highly competitive environment (e.g. Barker, 1998; Graaf, 2023).

Finally, one could also argue that the *negotiating* mode of boundary work emerged from an *opportunity tie,* which originated in the *coalescing* mode of boundary work. More specifically, the collaboration with AI specialists has given them the opportunity to shift their roles and conduct more technological activities. However, as mentioned earlier, this collaboration is something that analysts who work within larger firms have easier access to. Because of this, the opportunity tie between negotiating and coalescing does not exist for sell-side analysts in smaller firms without AI specialists, putting them at a disadvantage.

In summary, the interplay between negotiating and coalescing facilitates the effects of the creating mode of boundary work. As mentioned earlier, this helps sell-side analysts to navigate the competitive environment by having greater generative AI capabilities. This intertwined relationship between the boundaries and how they relate to competition is illustrated in figure 1.

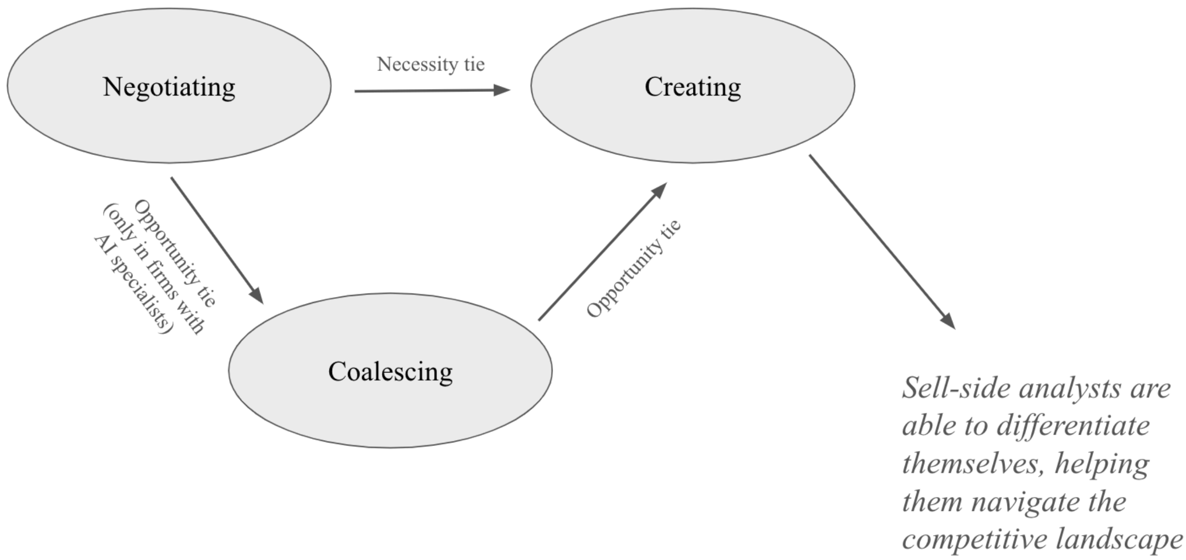

Figure 1: How intertwined boundary work influences the competition among sell-side analysts.

6. Conclusion

6.1 Summary

Overall, our study showcases how sell-side analysts implement generative AI tools, and how these tools impact them. When analyzing the responses of our ten interviewees through the framework of boundary work from Faulconbridge et al. (2023), we find that sell-side analysts primarily utilize generative AI as a starting point for time-consuming tasks such as finding peers, formulating texts and summarizing data and texts. These tools reduce the time required for these tasks, allowing sell-side analysts to spend more time on analyzing and interpreting this data. This gives an opportunity for the sell-side analysts to create a new group in which they are regarded as “superior” sell-side analysts. In order to reach this group, sell-side analysts experience a higher degree of collaboration with AI specialists. Furthermore, their role also shifts from mainly only conducting financial analyses, to additionally conducting more technological activities. These two different activities thus coalesce in a new space. However, the disruptive potential of these generative AI tools has also led to the notion that sell-side analysts could be replaced by these tools, or that they could help amateur investors compete with these sell-side analysts. To negate these beliefs and defend their position, sell-side analysts downplay the abilities of the generative AI tools, highlighting their own superiority to these machines. Moreover, through these findings, we also nuance previous research with two key contributions. Firstly, we contribute to previous research on how new digital technologies impact sell-side analysts. More specifically, we compare how generative AI impacts sell-side analysts with how previous innovations impact them, and how this affects their role as financial intermediaries. Secondly, we contribute to previous research on competition among sell-side analysts, by nuancing how generative AI interplays with previously researched phenomena and drivers of their competitive environment.

6.2 Limitations and suggestions for future research

Our study does have some limitations. Firstly, our study mainly focuses on sell-side analysts, with some contextual setting from specialists working with implementing generative AI in organizations. However, our study does not consider other perspectives from other actors in financial markets. Future research could benefit from interviewing other actors like investors and the clients of sell-side analysts to see if and how generative AI affects the output from sell-side analysts. Secondly, our study suggests that the generative AI literacy is low among sell-side analysts. However, our study does not research this field further. At the same time, this is something that we deem as important to further research the role of sell-side analysts. We embrace research that further investigates the generative AI literacy among sell-side analysts and its implication on their output quality. Thirdly, we encourage the research of the ethical considerations and regulatory challenges of implementing generative AI in financial analysis. This is because our study does not cover these areas, while still being a matter that is (i) an important consideration for the implementation of generative AI, (ii) mentioned by many of the interviewees, and (iii) not extensively researched in the sell-side analyst literature. Finally, another consideration with our study is that many of our sell-side analysts have few years of experience. Future research could contribute by nuancing this research by interviewing more experienced sell-side analysts.

7. References

Abbott, A. (1995). Things of boundaries. *Social Research* 62(1), 857-882.

Armstrong, R. (2018). The unmourned death of the sellside analyst. Financial Times.

Barker, R. G. (1998). The market for information - evidence from finance directors, analysts and fund managers. *Accounting and Business Research, 29*(1), 3-20. https://doi.org/10.1080/00014788.1998.9729563

Barnes, M.B., Lee, V.C.S. (2007). Feature selection techniques, company wealth assessment and intra-sectoral firm behaviours. Advanced Intelligent Computing Theories and Applications. With Aspects of Theoretical and Methodological Issues. *Lecture Notes in Computer Science, 4681*, 134-146.

Barredo Arrieta, A., Díaz-Rodríguez N., Del Sel, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information fusion*, 58(1), 82-115. https://doi.org/10.1016/j.inffus.2019.12.012.

Beunza, D., & Garud, R. (2007). Calculators, lemmings or frame-makers? The intermediary role of securities analysts. *The Sociological Review, 55*(2), 13–39. https://doi.org/10.1111/j.1467-954X.2007.00728.x

Bradshaw, M. T. (2009). Analyst information processing, financial regulation, and academic research. *The Accounting Review, 84*(4), 1073–1083. https://doi.org/10.2308/accr.2009.84.4.1073

Bradshaw, M. T. (2011). Analysts' Forecasts: What Do We Know after Decades of Work?. http://dx.doi.org/10.2139/ssrn.1880339

Bradshaw, M., Ertimur, Y., O'Brien, P. (2017). Financial Analysts and Their Contribution to Well-Functioning Capital Markets. *Foundations and Trends in Accounting 11*(3), 119-191. http://dx.doi.org.ez.hhs.se/10.1561/1400000042.

Brown L. D. (1993). Earnings Forecasting Research: Its Implications for Capital Markets Research. *International Journal of Forecasting, 9*(3), 295-320.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "Black Box" of sell-side Financial analysts. *Journal of Accounting Research, 53*(1), 1–47. https://doi.org/10.1111/1475-679X.12067

Bos-de vos, M., Lieftink, B. M. and Lauche, K. (2019). How to claim what is mine: Negotiating professional roles in inter-organizational projects. *Journal of Professions and Organization, 6*(1), 128-155.

Boussabaine, A. H., Kaka, A. P. (1998). A neural networks approach for cost flow forecasting. *Construction Management and Economics, 16*(1), 471-479.

Bucher S. V., Chreim, S., Langley, A., Reay, T. (2016). Contestation about collaboration: discursive boundary work among professions. *Organizations Studies, 37*(1), 1 649-1 672.

Burns, M. B., Igou A. (2019). "Alexa, Write an Audit Opinion": Adopting Intelligent Virtual Assistants in Accounting Workplaces. *Journal of Emerging Technologies in Accounting, 16*(1), 81-92. https://doi.org/10.2308/jeta-52424

Chen, B., Wu, Z., Zhao, R. (2023). From fiction to fact: the growing role of generative AI in business and finance. *Journal of Economic and Business Studies 21*(4), 471–496. https://doi-org.ez.hhs.se/10.1080/14765284.2023.2245279

Commerford, B., Dennis, S. A., Joe, J. R., Ulla, W. J. (2021). Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence. *Journal of Accounting Research, 60*(1), 171-201. http://dx.doi.org/10.1111/1475-679x.12407

Cote, J., Goodstein, J. (1999). A Breed Apart? Security Analysts and Herding Behavior. *Journal of Business Ethics, 18*(3), 305-314.

Creamer, G. G., Y. Freund (2010). Automated Trading with Boosting and Expert Weighting. *Quantitative Finance, 4*(10), 401-420.

DiCicco-Bloom, B., Crabtree B. F. (2006). The qualitative research interview. *Medical Education 40*(4), 314-321. https://doi.org/10.1111/j.1365-2929.2006.02418.x

Dorfman, J. R. (June 6, 1996). Ranking the Analysts. *The Wall Street Journal.* https://www.wsj.com/articles/SB838136739226885000.

Easley, D., O'Hara, M., Paperman, J., (1998). Financial analysts and information-based trade. *Journal of Financial Markets, 1*(2), 175-201. https://doi.org/10.1016/S1386-4181(98)00002-0

Faulconbridge, J. R, Spring, M., Atif, S. (2023). How Professionals Adapt to Artificial Intelligence: The Role of Intertwined Boundary Work. *Journal of Management Studies*. http://dx.doi.org/10.1111/joms.12936

Fogarty, T., Rogers, R., K. (2005). Financial analysts' reports: an extended institutional theory evaluation. *Accounting, Organizations and Society, 30*(4), 331-356.

Ghasemi, M., Shafeiepour, V., Aslani, M. & Barvayeh, E. (2011). The impact of Information Technology (IT) on modern accounting systems. *Procedia - Social and Behavioral Sciences, 28*(1), 112–116. https://doi.org/10.1016/j.sbspro.2011.11.023

Graaf J. (2023). Can Sell-side Analysts Compete Using Public Information? Analysts as Frame-makers Revisited. *European Accounting Review, 32*(1): 141-167.

Granlund, M., & Mouritsen, J. (2003). Special section on management control and new information technologies. *European Accounting Review, 12*(1), 77–83. https://doi.org/10.1080/0963818031000087925

Grossoehme, D. H. (2014). Overview of Qualitative Research. *Journal of Health Care Chaplaincy, 20*(3), 109-122.

Hägglund, P. (2000). The value of facts: How analysts' recommendations focus on facts instead of value'. In Kalthogg, H., Rottenburg, R., Wagener, H. J. (Eds.), *Ökonomie und geschellschaft* (pp. 313–337). Metropolis Verlag.

Hirst, D. E., Koonce, L., Simko, P. J. (1995). Investor Reactions to Financial Analysts' Research Reports. *Journal of Accounting Research, 33*(2), 335-351. https://doi.org/10.2307/2491491

Holland J., (1998) Private disclosure and financial reporting. *Accounting and Business Research, 28*(4): 225-269.

Imam, S., Spence, C. (2016). Context, not predictions: A field study of financial analysts. *Accounting, Auditing & Accountability Journal,* 29(2), 226–247. https://doi.org/10.1108/AAAJ-02-2014-1606

Jones, M. J., Shoemaker, P. A. (1994). Accounting narratives: A review of empirical studies of content and readability. *Journal of Accounting Literature, 13*(1), 142.

Karaca, I., Gransberg, D. D., Jeong, H. D. (2020). Improving the accuracy of early cost estimates on transportation infrastructure projects. *Journal of Management in Engineering, 36*(5),

Kothari, S. P. (2001). Capital markets research in accounting. *Journal of Accounting and Economics, 31*(1-3), 105-231.

Krishnan, R., Booker, D. M. (2002). Investors' Use of Analysts' Recommendations. *Behavioral Research in Accounting, 14*(1), 129-156. https://doi.org/10.2308/bria.2002.14.1.129

Kuperman, J. C., Athavale, M., Eisner, A. (2003). Financial analysts in the media: Evolving roles and recent trends. *American Business Review 21*(2), 74.

Kurljusic, M., Karger, E. (2023). Forecasting in financial accounting with artificial intelligence - A systematic literature review and future research agenda. *Journal of Applied Accounting Research, 25*(1), 82-104.

Langley, A., Lundberg, K., Mørk, B. E., Nicolini, D., Raviola, E., Walter, L. (2019). Boundary work among groups, occupations, and organizations: From cartography to process. *Academy of Management Annals, 13*(1), 704-736.

Lang, M. H., and R. J. Lundholm (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review, 71*(4): 467-492.

Lin H., McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, 25(1), 101-127.

Maksymov, E., Pickerd, J., Lowe, J. D., Peecher, M. E., Reffett, A. (2019). The Settlement Norm in Audit Legal Disputes: Insights from Prominent Attorneys. *Contemporary Accounting Research 37*(3), 1400-1443.

Moyer, R. C., Chatfield, R. E., Sisneros, P. M. (1989). Security Analyst Monitoring Activity: Agency Costs and Information Demands. *Journal of Financial and Qualitative Analysis, 24*(4), 503-512.

Muzio, D., Brock, D. M., Suddaby, R. (2013). Professions and institutional change: Towards an institutionalist sociology of the professions. *Journal of Management Studies, 50*(1), 699-721.

Noordegraaf, M (2020). Protective or connective professionalism? How connected professionals can (still) act as autonomous and authoritative experts. *Journal of Professions and Organization, 7*(1), 673-695.

Önkal, D., Goodwin, P., Thomson, Gönül S., Pollock M. (2009). The Relative Influence of Advice from Human Experts and Statistical Method on Forecast Adjustments. *Journal of Behavioural Decision Making, 22*(1), 390-409.

Pathank, V., Bijayini, J., Sanjay, K. (2013). Qualitative research. *Perspectives in Clinical Research, 4*(3), 192. http://dx.doi.org/10.4103/2229-3485.115389

Porter, M. E., Heppelmann J. E. (2015). How Smart, Connected Products Are Transforming Companies. *Harvard Business Review*, 96-112, 114.

Quick, K. S., Feldman, M. S. (2014). Boundaries as junctures: Collaborative boundary work for building efficient resilience. *Journal of Public Administration Research and Theory, 24*(1), 673-695.

Ramnath, S., Rock, S., Shane, P. (2008). The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research. *International Journal of Forecasting, 24*(1), 34-75.

Schipper (1991). *Analysts' forecast. Accounting Horizons, 5*(4), 105-121.

Schlienkamp, C. (2002). Was Analysten sagen, was Analysten meinen. Die Kommunkikationsregeln der Community in B. Kirf & L. Rolke (Eds.). Der Stakeholder-Kompass. *Navigationsinstrument für die Unternehmenskommunikation*, 168-176.

Soltes, E. (2014). Private Interaction Between Firm Management and Sell-Side Analysts. *Journal of Accounting Research, 52*(1), 245-272.

Spence, C., Aleksanyan, M., Millo, Y., Imam, S., & Abhayawansa, S. (2019). Earning the 'write to speak': Sell-side analysts and their struggle to be heard. *Contemporary Accounting Research, 36*(4), 2635–2662. https://doi.org/ 10.1111/1911-3846.12496

Suddaby, R., Viale, T. (2011). Professionals and field-level change: *Institutional work and the professional project. Current sociology, 59*(1), 598-618.

Swanson, R. A., Holton III, E. F. (2005). *Research in organizations: Foundations and methods of inquiry*. Berrett-Koehler Publications.

Vollmer, H., Mennicken, A., & Preda, A. (2009). Tracking the numbers: Across accounting and finance, organizations and markets. *Accounting, Organizations and Society, 34*(5), 619–637. https://doi.org/10.1016/j.aos.2008.06.007

Whitehouse, M. (2018). Financial Analysts and Their Role in Financial Communication and Investor Relations. In Laskin, A. V. (2017). *The Handbook of Financial Communication and Investor Relations* (117-126). John Wiley & Sons.

Zietsma, C., Lawrence, T. B. (2010). Institutional work in the transformation of an organizational field: The interplay of boundary work and practice work. *Administrative Science Quarterly, 55*(1), 189-221.

8. Appendix

8.1 Appendix 1: Interviews

Table 1: A short description of each interviewee and company is summarized in this table

Date of Interview	Length	Interviewee	Relevant work experience	Business Area	AI experience*
12/03/24	01:04	Analyst 1	5 years	Financial Advisory	Low
12/03/24	01:04	Analyst 2	2 years	Financial Advisory	Medium
01/04/24	0:57	Analyst 3	1 year	Institutional sales	Low
05/04/24	0:45	AI specialist 1	12 years	Data Scientist	High
07/04/24	0:27	Analyst 4	1 year	Investment Banking	Low
08/04/24	0:39	Analyst 5	1 year	Investment Banking	Low
10/04/24	0:43	AI specialist 2	13 years	Data and Technology Director	High
13/04/24	0:28	Analyst 6	1 year	Financial Advisory	Medium
18/04/24	0:36	AI specialist 3	9 years	Data Scientist	High
18/04/24	0:28	Analyst 7	4 years	Investment Banking	Medium

* Note that this is graded based on our interpretation of the interviewees' AI experience (see section 3.3).

8.2 Appendix 2: Interview Guide for Analysts

Before start

- Revise the confidentiality clarifications of the interview and the rights according to GDPR. Ask for permission to record the interview
- Briefly introduce ourselves and our study. Inform about the length of the interview and the format.

Introduction/background

- Can you briefly introduce yourself?
- What are your daily tasks?
- What are your most difficult tasks in your job? Is there any part of the job that you dislike? E.g. if there are any cumbersome/time-consuming tasks of your job (or in your team).
- How many are in your department/team? Do you cooperate with a lot of your team members?

Generative AI

- How familiar are you with AI and generative AI? How much do you know about how your generative AI tools actually work?
- How do you and others use generative AI within your role? How has this changed over the past few years? What tools do you use? How do they help you?
- Are there other forms of tools which you know are used by other departments, or throughout the whole company?
- How do you value the information from a generative AI tool? Do you view it with some skepticism, or do you value it as similar compared to other sources of input? How do you think your client views you using AI?
- Has the perception of AI and generative AI changed over time for you and your team? Do you believe that there is a change after the increased usage of generative AI?
- What do you see as shortcomings of using generative AI within your work? Any potential risks?
- What do you see as the greatest benefits that generative AI will bring to your work?
- How do you think generative AI will affect your industry? How do you think generative AI will impact your job 10 years in the future?

Wrap-up

- Thank for the interview
- Do you have any questions?

8.3 Appendix 3: Interview Guide for AI Specialists

Before start

- Revise the confidentiality clarifications of the interview and the rights according to GDPR. Ask for permission to record the interview
- Briefly introduce ourselves and our study. Inform about the length of the interview and the format.

Introduction/background

- Can you briefly introduce yourself?
- What are your daily tasks?

Generative AI

- How do you specifically help your customers implement generative AI?
- How knowledgeable do you find your customers to be within generative AI?
- How familiar are you with AI and generative AI?
- How do you use generative AI?
- How do you value the information from a generative AI tool? Do you view it with some skepticism, or do you value it as similar compared to other sources of input? How about your customers?
- Has the perception of AI and generative AI changed over time for you and your team? Do you believe that there is a change after the increased usage of generative AI? What about with your customers?
- What do you see as shortcomings of using generative AI? Any potential risks? What about for your customers?
- What do you see as the greatest benefits of using generative AI? What about for your customers?
- How do you think generative AI will affect the financial analysis industry? How do you think generative AI will impact your job 10 years in the future? What about the jobs of your customers?

Wrap-up

- Thank for the interview
- Do you have any questions?