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HOW DOES INTEGRATED REPORT QUALITY AFFECT DECISION-MAKING? AN EQUITY ANALYST PERSPECTIVE IN THE SOUTH AFRICAN MARKET

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Notes:

1. Two abstracts from the research in this thesis were presented at the following conferences:

   a. The 2023 Stellenbosch Business School Corporate Governance Conference
   b. The 2024 Southern African Finance Association's Conference

   The authors acknowledge the feedback provided by the participants at the conferences. Extracts from the Book of Abstracts distributed at the conferences are provided in Appendix O of this document.

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Glossary of terms

Term	Definition
Buy-side Equity Analyst	Buy-side equity analysts work for asset management companies and make internal recommendations and forecasts exclusively for money managers (Cheng, Liu & Qian, 2006).
Cognitive bias	A deviation from rationality that arises because the human cognitive system makes inferences about situations based on imperfect cues (Tversky & Kahneman, 1974).
Commissioned / Sponsored Research	Commissioned research is equity research provided by analysts but paid for by the company that is the subject of the research. Companies usually pay for research to enhance their visibility to investors, thereby enhancing the liquidity of their shares. (Kline, 2015)
Composite reliability/ Construct reliability	A measure of internal consistency in scale items or measurement indicators (Kline, 2015)
Construct reliability	The extent to which items that measure a construct are similar in their scores (Kline, 2015)
Content Elements (CE)	A content element is a specific type of detail about the company that must be discussed in its integrated report. There are eight[1] content elements that are required according to the International Integrated Reporting Framework (IIRC, 2021).
Convergent validity	A category of construct validity. The extent to which indicators of a specific construct share common variance (Hair *et al.*, 2019)
Discriminant validity	The extent to which constructs are sufficiently distinct from other constructs (Hair *et al.*, 2019)
Fundamental Concepts (FC)	Fundamental Concepts underpin the requirements of the Integrated Reporting Framework. They relate primarily to the manner in which a company creates, maintains or destroys value using economic, social and natural capitals (IIRC, 2021).
Guiding principles (GP)	The seven guiding principles provided in the Integrated Reporting Framework direct the preparation and presentation of an integrated report (IIRC, 2021).
Institutional investors	Institutional investors are asset management companies, such as mutual funds and insurance companies. They manage investments on behalf of their clients (Chaudhury, Sahoo & Dawar, 2022).

[1] Details of the content elements, fundamental concepts and guiding principles are provided in Appendix A: Extracts from Integrated Reporting Framework

Term	Definition
Integrated Report (IR)	A concise communication about how an organisation's strategy, governance and performance leads to the creation of value (IIRC, 2021). The report contains financial and non-financial information and is issued annually by the company.
International Integrated Reporting Framework	A framework issued by the International Integrated Reporting Council to enable more decision-useful reporting (IIRC, 2021).
Measurement model	A model that shows how constructs are created from a set of measurement indicators or observed variables (Hair *et al.*, 2019). See also "Structural Equation Modelling"
Sell-side Equity Analyst	Equity analysts who work for brokerage firms and conduct research for their firms' clients. Their research is also available to the public (Cheng, Liu & Qian, 2006).
Structural Equation Modelling (SEM)	Structural Equation Modelling is a method for analysis that combines factor analysis, path analysis and regression analysis to evaluate the reliability and validity of the measurement model and validate relationships amongst theoretical constructs (Kline, 2015).
Structural Model	A model which tests hypothetical dependencies based on path analysis (Kline, 2015)

List of abbreviations and acronyms

Abbreviation/ Acronym	Term
AR	Annual Report
ESG	Environmental, Social and Governance
IFRS	International Financial Reporting Standards
IIRC	International Integrated Reporting Council
IR	Integrated Report
PLS	Partial Least Squares
SEM	Structural Equation Model
SENS	Stock Exchange News Service

Abstract

A key source of information about a company is their integrated reports, whose main purpose is to improve the quality of information available to investors. Seminal behavioural finance literature shows that, in situations where market participants perceive potentially imperfect information, they may be inclined to behavioural biases in their estimation of the value of a firm's shares. However, prior literature also shows that behavioural bias may be present even when there are no evident deficiencies in the information environment. This study explores the relationship between the quality of integrated reports and behavioural bias in the South African equity market. Integrated report quality is approximated by the scores awarded by adjudicators of the EY Excellence in Integrated Reporting Awards. The study focuses on sell-side equity analysts as market participants. A convergent mixed methods design was used. Quantitative analysis was in the form of a structural equation model with latent variables for quality and each of the behavioural biases. The model incorporated data from 2208 forecasts from 316 analysts, across 342 company-years. Semi-structured interviews with 20 sell-side equity analysts were conducted to provide the context necessary for a meaningful evaluation. Across all methods of analysis, findings show that the quality of information in the integrated reports has little to no effect on the analysts' decision-making processes. Findings from the interviews indicate that analysts consider direct interactions with management to be the most important source of information for their reports and forecasts. In these interactions, they rely on "gut feel" to establish credibility of management's assertions. Regarding bias, the quantitative analysis showed that herding has a negative and significant association with the quality of analysts' forecasts. The qualitative analysis confirmed the analysts' view of the consensus forecast as a benchmark. Considered with findings of the lack of use of integrated reports, it is inferred that analysts view the consensus forecast as a more useful source of information than the information in the integrated reports. Despite the use of indicator variables with prior literature as precedent, the results of the analysis can vary depending on the choice of measurement approximations for the behavioural biases. The study makes a theoretical contribution by connecting research on integrated report quality and behavioural bias. It shows that analyst coverage, even if sponsored by the company, is considered necessary to reduce information asymmetry, despite the production of integrated reports. The study makes a methodological contribution with its analysis of qualitative data from interviews with analysts. Based on the findings, it considers how general debiasing strategies could be used in the context of analysts, thereby making a practical contribution.

Keywords: Integrated reporting, Analysts, Behavioural bias, Information environment, Mixed methods

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Chapter 1: Introduction

1.1. Background and overview

The consumption of information by investors forms the basis for the work on market efficiency (Fama, 1970). It is well known that markets in which asset prices reflect all available information are considered efficient, at least from a theoretical perspective. Information is therefore both important and valuable, to the extent that all available information is correctly analysed and acted upon, thereby creating a price reflective of such actions. Stiglitz (2017, p. 2) emphasised the importance of information in financial markets when he explained:

"The financial sector is above all else, about gathering and processing information, on the basis of which capital resources can be efficiently allocated".

Research on information economics focuses on information as a public good with producers and consumers (Stiglitz, 2017). Extending this metaphor, the presence of poor-quality information is likely to lead to an increase in the cost of *good* information (as explained in Akerlof, 1978) or, at the very least, scepticism in the minds of consumers. Furthermore, asymmetries in information result when the producers of information have not conveyed all known information to consumers. These issues are particularly relevant in the context of the firm whose structure is characterised by the separation of managers and owners. In this context, the role of the accountant has been to provide information that enables holding management to account and is useful to the market. This information, in the form of Integrated Reports, is disseminated to facilitate the informed decision-making of investors.

An Integrated Report is a recent development in corporate reporting (Pistoni, Songini & Bavagnoli, 2018). It combines financial, governance, social and environmental information in a single report (Eccles, Krzus & Solano, 2019). For companies listed on the Johannesburg Securities Exchange (JSE), the production of an Integrated Report is considered effectively mandatory. This is because the JSE Listing Requirements require the application of the King Codes on Corporate Governance (in particular, King III, effective from March 2010), where Integrated Reporting is recommended. Companies which do not produce Integrated Reports are required to explain why they have not done so[2], effectively making their production a requirement of the JSE (Barth, Cahan, Chen & Venter, 2017). Although integrated reporting is mandated in South Africa, companies in several other countries produce the reports voluntarily. The countries include fellow developing economies such as India and China (Barth *et al.*, 2017), and developed economies such as the United States of America and the United Kingdom (Eccles *et al.*, 2019).

The rationale that integrated reporting can reduce information asymmetry is premised on the assumption that improved information disclosure reduces uncertainty and risk. In Eccles *et al.* (2019, p.1), the producers of the first company integrated reports are described as "corporate pioneers" who provided information that would improve their shareholders' understanding of the company. The information requirements of capital providers are reiterated by the International

[2] According to Abhayawansa, Elijido-Ten and Dumay (2019 p.1616), "institutional pressures are coercing companies to produce an integrated report" in South Africa.

Integrated Reporting Council (IIRC). The IIRC is a coalition of regulators, accounting standard setters, investors and other market participants (IIRC, 2021). Using the International Integrated Reporting Framework, the council promotes the publication of integrated reports by companies. Its primary purpose is to:

"Improve the quality of information available to providers of financial capital to enable a more efficient and productive allocation of capital". (IIRC, 2021)

A key motive of integrated reporting is therefore the improvement of the information environment for its defined primary users - providers of financial capital (Zhou, Simnett, & Green, 2017). However, researchers have debated the quality of information contained in integrated reports (Atkins & Maroun, 2015; Pistoni, Songini, & Bavagnoli, 2018; Eccles *et al.*, 2019). In their interviews of institutional investors, Atkins and Maroun (2015) found that the length of reports, repetition and a check-box approach detract from the usefulness of integrated reports to institutional investors. Whilst Barth *et al.* (2017) found evidence of improved decision-making within organisations that adopted integrated reporting, there was no association between integrated reporting and analysts' forecast accuracy. Pistoni *et al.* (2018) found that integrated reports lacked important information on capital, business models, strategic priorities and the value creation process. The depth of analysis was also found to be lacking and the authors concluded that more attention is given to the form of the report instead of its contents.

The present study considers the prior findings regarding the useful of integrated reports, with a particular focus on equity analysts. Equity analysts are classified as either buy-side analysts or sell-side analysts. Both buy-side and sell-side equity analysts provide financial forecasts and buy, hold or sell recommendations (or equivalent) for publicly traded companies, although they serve different clients (Cheng, Liu & Qian, 2006). Sell-side analysts release their earnings and share price predictions and recommendations to other institutional investment companies and the public (via databases such as Bloomberg). Buy-side analysts are employed by institutions, such as fund management firms that make investments in other companies. The results of the buy-side analysts' research are not made public and is for the sole use of their employer, in making investment decisions (Cheng *et al.*, 2006).

Sell- side analysts are regarded as key participants in the financial market (Cen, Hilary, & Wei, 2013; Du & Budescu, 2018). They are described as "information intermediaries" (Du & Budescu, 2018) as they provide interpretations of fundamental information for the investment decision to be made. Therefore, the research that connects financial analysts' information requirements to the information provided in integrated reports is key to the evaluation of the informational efficiency of capital markets. Financial analysts are regarded as sophisticated users of corporate reports. They are more likely to use the information provided in corporate reports to inform their evaluations and recommendations (Flores, Fasan, Mendes-da-Silva, & Sampaio, 2019). Their reports are a description of the cognitive processes involved in the collection, interpretation and distribution of information regarding a firm's future performance (Asquith, Mikhail, & Au, 2005).

Tversky and Kahneman (1974) explain that heuristics are employed to assess probabilities in situations of uncertainty. In situations where market participants perceive potentially imperfect information, they may be inclined to certain heuristics in the estimation of a true value of the firm's shares, especially if the participants' intention is to outperform the market. The cognitive processes of analysts are important to evaluate as they may provide an indication of the contextual factors that increase proclivity for bias. This is an interesting basis for research, given the findings by Barth *et al.* (2017) and Zhou *et al.* (2017) is that poor information quality results in increased forecast error amongst analysts.

Yet, forecast errors cannot be attributed solely to inadequacies of financial reports. The application of cognitive psychology research to the decision processes of analysts has suggested that heuristics may also be applied in situations where there are no evident deficiencies in the information available. Hirshleifer, Lourie, Ruchti, and Truong (2020) find evidence of confirmation bias amongst equity analysts. Their research shows that equity analysts give a higher weighting to their first impressions of a firm. For firms that performed well when the analyst first began following it, the analyst will tend to overweight any positive information about the firm in the future. Analysts' incentives for career progression (Hong & Kubik, 2003; Roger, Roger, & Schatt, 2018) may also influence their forecasts. They are likely to be over-optimistic in firms where they are rewarded for producing more "buy" forecasts. This conflict is particularly relevant if their employer has an existing relationship with the subject company (Mokoaleli-Mokoteli, Taffler, & Agarwal, 2009).

The estimation of future earnings is a complex task and involves a high degree of uncertainty. Therefore, forecast errors also stem from heuristics that are employed to reduce cognitive load either *because* of the abundance of information or *despite* the abundance of information. Pascual-Ezama, Paredes, and de Liaño (2018) show that even more educated investors resort to "intuitions" or heuristics when provided with various sources of information. They call for shorter and simpler reports of financial information to facilitate a more efficient allocation of resources in the capital market. This sentiment appears to extend beyond the academic research as users of financial information acknowledge the complexity of reports that are currently produced (Joffe, 2020).

Behavioural biases can also occur purely because of flaws in the way the mind processes information. Roger *et al.* (2018) find that analysts process small numbers differently from large numbers. Whereas small numbers are processed on a linear scale, large numbers are processed on a logarithmic scale. This extends to the processing of share prices. Optimistic analysts issue more optimistic price targets on small price shares and pessimistic analysts issue more pessimistic targets on small price shares. These types of biases are likely to be exacerbated because of the complexity and abundance of information provided in corporate reports.

The market reaction to information, either directly from corporate reports or from analysts' reports, has been shown to vary, sometimes in ways that cannot be directly attributed to the information provided. Besides potentially having their own biases (De Bondt & Thaler, 1985), market participants may be influenced by the biases of financial analysts (Cen *et al.*, 2013) and may respond with trading strategies that exploit the opportunities presented by a potential mispricing. Alternatively, the market may also display the same bias as the analysts, thereby contributing to the mispricing. It is also possible that the market responds appropriately to the potential contribution of integrated reports to the information environment, resulting in lower asymmetries (Barth *et al.*, 2017).

This study connects the economic theories of information asymmetry and market efficiency to the issues with the quality of information by tracing the flow of information from preparation within organisations to consumption in the capital markets. The literature on the information environment provides a framework from which to evaluate the sources of these uncertainties.

1.2. Problem Statement

Behavioural Finance research shows that the proclivity to heuristics and behavioural bias is increased when judgement is made under uncertainty (Tversky & Kahneman, 1974). Despite the production of Integrated Reports to reduce uncertainty and information asymmetry, market participants and researchers appear to have doubts about the quality and relevance of the information contained in integrated reports. There appears to be a lack of clear evidence of its benefits (Zhou *et al.*, 2017). Users of accounting information still bemoan its complexity and lack of relevance to decision-making (Joffe, 2020).

In addition, doubts from the market are exacerbated in the context of recent audit and corporate governance failures (Rossouw & Styan, 2019; Crotty, 2020; Marchant, 2020). An example is the accounting irregularities at Tongaat Hulett. These accounting irregularities were uncovered early in 2019 and related to several previous years (Marchant, 2020). Interestingly in 2018, audit firm EY rated Tongaat Hulett's integrated report as "Good", the second highest rating behind "Excellent" in their annual Integrated Reporting Awards (EY, 2018, p.6).

Yet, the research on analysts' decision-making processes and capital market behaviour indicates that possible market inefficiencies cannot be attributed entirely to a lack of information or deficiencies in information (Asquith *et al.*, 2005; Hong & Kubik, 2003; Lötter, 2018; Roger *et al.*, 2018). Analysts are also prone to bias due to cognitive limitations. Tversky and Kahneman (1974) showed that in situations of uncertainty, heuristics are employed to ease cognitive load. This research is primarily motivated by the need to understand and manage behavioural biases that are triggered by the uncertainties in the capital market. It evaluates the role of behavioural bias in the contexts of the uncertainty that remains despite the current corporate reporting practices, thereby responding to the call by Malmendier (2018) and Ahmad (2020) to delve deeper to find the possible root cause of the bias.

Considering the information environment and market efficiency, Barker (1998) explains that relevant information may exist in the market that is not reflected in share prices, either because it *has not been made available* or because it *has not been processed correctly (emphasis added)*. The present study explores each of these two possibilities. The first possibility, being the inadequacy of information, is investigated by exploring the relationship between integrated reporting and analyst forecast accuracy. The second possibility, that of information being processed incorrectly, is investigated by exploring the relationship between biases and analyst forecast accuracy. Though these may seem like separate objectives, they are linked through the notion from Tversky and Kahneman (1974) that uncertainty increases proclivity to bias, and integrated reports are intended to reduce uncertainty in the capital markets.

In response to this, the present research aims to understand the possible drivers of uncertainty and bias in the flow of information through the market. The central notion of this study is that the performance of a company's shares may be influenced by the corporate information, specifically integrated reports, provided as well as the manner in which the information is utilised. Lastly, the research sought to determine whether any possible biases affect the allocation of resources in the market by analysing the performance of the shares of companies in response to the information produced by the company and its analyst followers.

1.3. Thesis statement

In situations of imperfect information (or uncertainty), market participants are more inclined to the use of heuristics (and resulting behavioural bias) in the estimation of a "more accurate" value (Tversky & Kahneman, 1974). Stiglitz (2000, p.1469) calls for further research on "how knowledge is disseminated, absorbed and used". This dissemination, absorption and use of information provides the basis for the thesis statement of this study:

The quality of integrated reports impacts the information environment in the equity capital markets. Where the information environment is poor, investors will resort to the use of heuristics in their decision-making.

1.4. Information environment

The efficiency of capital markets has been debated in academic literature ever since the seminal work by Fama (1970). The preparation and dissemination of perfect information is central to the hypothesis; when information becomes available it is disseminated rapidly and is incorporated into share prices. As a result, prices fully reflect all known information. However, variations in the quality of the information may increase information asymmetries in the market.

Healy and Palepu (2001) consider the "lemons" problem (Akerlof, 1978) in the context of information required for the investment decision. They contend that if investors cannot distinguish between good and bad categories of businesses in which to invest, then managers with bad businesses may assert themselves as good businesses, and the converse will apply to managers of good businesses. In response, investors will assign an average value to both positive and negative ideas. Consequently, if the issue of distinguishing good from bad businesses is not entirely resolved, the capital market will logically undervalue some positive ideas and overvalue some negative ideas compared to the information accessible to managers.

There is no dearth of research on the quality of corporate reports and their usefulness in reducing information asymmetry (Haji & Anifowose, 2016; Barth *et al.*, 2017; Pistoni *et al.*, 2018). We extend the existing literature on the information environment by exploring its implications for financial analysts' forecast accuracy. We attempt to achieve this by evaluating the association between integrated report quality and analysts' forecasts. Brennan and Merkl-Davies (2018) considers the accountant as the communicator of information that influences human behaviour. Therefore, the manner in which the recipient comprehends the messages is a key determinant of the dynamics of the communication process. It is this cycle of communicating and receiving of corporate information, or the information environment, that is the "golden thread" for this study.

Sell-side equity analysts have a key role to play in the information environment – they are commonly studied as recipients of information (Harris & Wang, 2019; Ahmed & Flint, 2020). However, they are also regarded as information intermediaries as they can provide new information to the market, based on their own interpretations of accounting information (Asquith *et al.*, 2005). The manner in which they comprehend corporate information therefore has significant potential to influence the quality of the information environment. The process whereby they comprehend information from the firm has been the focus of behavioural finance researchers. Research on analyst recommendations shows that equity analysts are prone to behavioural bias (Lötter, 2018). The effect of integrated report quality on their proclivity for bias is also examined in this research, as part of the study of the information environment.

In light of the literature on information asymmetry and the quality of corporate reports, this study contributes to research on how deficiencies in information (from the corporate reporting literature) and limitations in cognitive abilities (from the behavioural finance literature) impact resource allocation in the financial markets. Specifically, this study examines the effect of integrated report quality and behavioural bias on the forecast recommendations of sell-side equity analysts.

1.5. Research objectives

The "information environment" provides a conceptual nexus for the somewhat isolated strands of research on corporate reports, analysts' use thereof and behavioural bias. Combining these strands of research, the present study examines the role of accounting information (integrated reports, in particular) in improving forecast accuracy. The widely cited work of Barth *et al.* (2017) found positive associations between integrated report quality and liquidity and future cash flows, respectively. However, Willows and Rockey (2018) found a stronger market reaction to the release of financial results in the annual report than to the release of integrated reports. Mokabane and du Toit (2022) affirmed the latter findings when they found no association between the quality of integrated reports and indicators of internal financial performance. They went on to postulate that the production of integrated reports is possibly an exercise in organisational legitimacy and impression management. The diverse evidence on the value of integrated reports provides the initial indication of remnants of information asymmetry in the market and warrants further investigation.

Therefore, Research Question 1 [RQ1] is: What is the effect of the quality of integrated report information on the market?

To investigate further, separate hypotheses were created for analysts, who are regarded as sophisticated users of financial information and for the information environment of the market as a whole.

H1: The quality of equity analysts' forecasts improves with an increase in the quality of information in the integrated reports.

As a measurement approximation for information asymmetry, the forecasts of equity analysts is analysed. Equity analysts are more likely to use the fundamental information provided in the corporate reports (Asquith *et al.*, 2005). We therefore specify the following sub-hypothesis:

> H1.a. The quality of information contained in a company's integrated reports has a positive relationship with the quality of analysts' forecasts for that company.

The use of analysts as a representative proxy for decisions in the equity market depends on the extent to which their recommendations influence investment choices in the rest of the market. Balakrishnan, Shivakumar and Taori (2021) find analysts' estimates of the cost of equity to be a reliable proxy of expected return. They note that analysts' estimates of the cost of capital are less noisy predictors of returns than the implied cost of capital (Balakrishnan *et al.*, 2021). However, the impact of analyst recommendations on share price performance has been debated (De Bondt & Thaler, 1990; Harris & Wang, 2019; Kim, Ryu, & Yang, 2019). In addition, analysts' recommendations are not solely driven by information contained in the integrated reports. Their recommendations are influenced by incentive conflicts (Hong & Kubik, 2003; Bradshaw, 2013) and behavioural bias (De Bondt & Thaler, 1990; Hilary & Menzly, 2006; Mokoaleli-Mokoteli *et al.*, 2009; Du & Budescu, 2018). A detailed evaluation of the effect of these factors on analysts' recommendations is deferred to future research. To examine the effect of integrated report quality on the information environment as a whole, we include the following sub-hypothesis:

> H1.b. The quality of information in a company's integrated reports has a positive relationship with share price performance of that company.

Secondly, the study focused on the way in which the information is used in the forecasting process. It's aim is to evaluate the influence of behavioural bias on the decision processes of investors.

Research Question 2 [RQ2]: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias?

H2: Poor quality integrated reports increase analysts' proclivity to behavioural bias.

For H2, we test the relationship between the quality of integrated reports and *each* bias.

Research Question 3 [RQ3]: What is the effect of behavioural bias on analysts' forecast decisions?

H3. The behavioural bias of equity analysts has an effect on the quality of their forecast decisions.

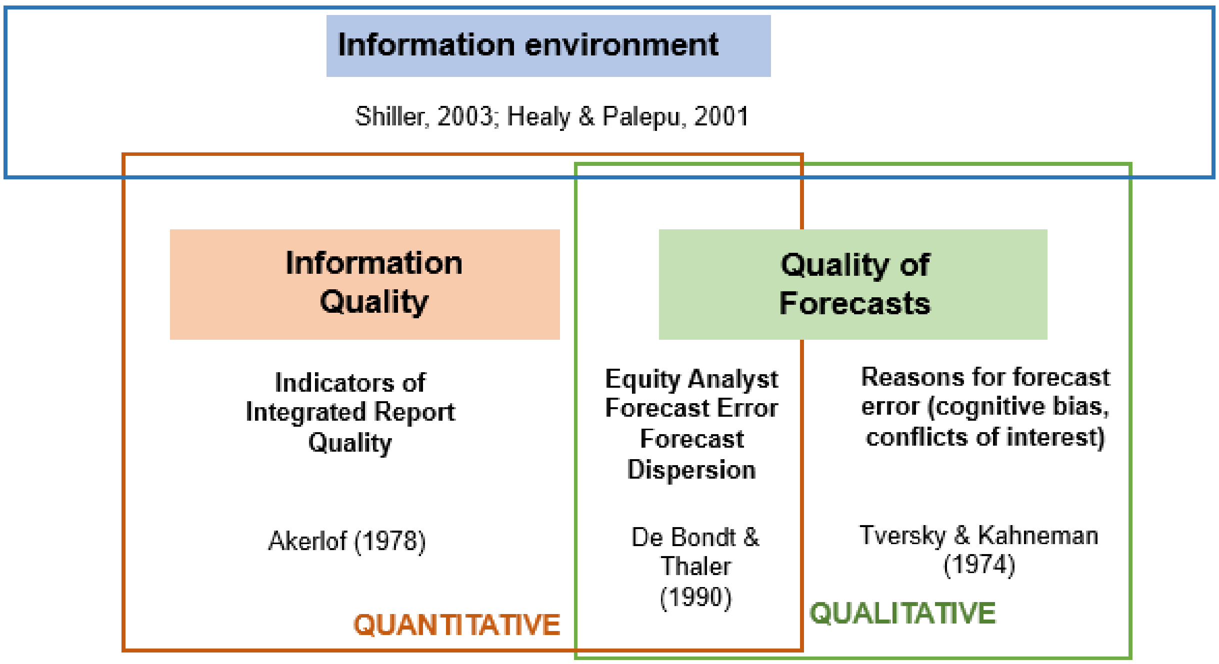
For H3, we test the relationship between *each* bias and the quality of analysts' forecasts.

RQ1 and RQ3 (and related hypotheses) refer to the quality of analysts' forecasts instead of merely the accuracy of analysts' forecasts. Quality of forecasts comprises both analysts' accuracy and dispersion of forecasts amongst analysts. This measure is intended to provide an indication of the information environment (Healy & Palepu, 2001) in which analysts must provide recommendations. In summary, the research traces the flow of information from the initial preparation by companies to consumption, by equity research analysts and ultimately, by the market.

1.6. Outline of the study

In light of the possibility of deficiencies in the information environment (Healy & Palepu, 2001; Zhang, 2006), market participants may overlay their own behavioural biases, especially if their intention is to outperform the rest of the market (Tversky & Kahneman, 1974). In other words, users may be prone to bias as they compensate for the lack of/ perceived lack of information. The study therefore also focuses on the quality of information as well as the biases of the consumers of financial information. Analysts were chosen to represent consumers of information, considering the literature on their processes, especially the evidence that they are sophisticated users of company financial information and are themselves disseminators of information (Asquith *et al.*, 2005; Zhang, 2006).

Figure 1: Outline of the study



Source: Author's own

Figure 1 is a depiction of the seminal work that motivated the study and its design. The researcher sought to understand the information environment, and the contributions of information quality and analyst bias to that information environment.

This study is structured across five chapters. An overview of each chapter is provided in the following paragraphs.

Chapter 1: Introduction

The first chapter presents a thesis statement, the background and purpose of the study. The information environment, the common thread throughout this study, is introduced. Research objectives are set, and key contributions are outlined.

Chapter 2: Literature review and hypothesis development

This chapter presents research from the corporate reporting and behavioural finance disciplines, with a focus on the role of analysts in the information environment. From a corporate reporting perspective, this section discusses literature on the purpose of integrated reports in the information environment. It then progresses to the role of sell-side equity analysts, with a focus on their dual roles as consumers and producers of information. From the perspective of the consumption of information, the theoretical framework and prior literature are mobilised in the development of the first set of hypotheses. These hypotheses relate the quality of information in the integrated report to the quality of the information environment.

Studies on the role of analysts as producers of information are used to develop the remaining sets of hypotheses, The second set of hypotheses draws on the behavioural finance studies as they relate integrated report quality to the proclivity for bias. Finally, the third set of hypotheses uses the same literature as it relates bias to the quality of analysts' forecasts.

The section also includes a review of the literature with focus on the methodologies used in the various strands of research.

Chapter 3: Methodology

This chapter begins with a discussion on the pragmatic paradigm, which was deemed most appropriate for this study. The chapter proceeds to present the concurrent triangulation design and motivate the researcher's choice thereof, given the research objectives. Being a mixed methods study, each major section of the methodology chapter deals with quantitative and qualitative data and methods of analysis.

Chapter 4: Results

This chapter addresses the research objectives by firstly presenting the qualitative analysis and results, being insights from interviews with analysts. Secondly, the results of the structural equation model are presented and discussed in relation to the hypotheses. Being a mixed method study, the chapter ultimately presents a synthesis of results from the qualitative and quantitative analyses.

Chapter 5: Conclusions and areas for future research

The final chapter begins by reflecting on the research objectives described in Chapter 1. The contributions of the study that were briefly outlined in the first chapter are discussed in detail, with reference to the results of the study. Finally, the limitations of the study are acknowledged and areas for future research are developed.

1.7. Contributions of the study

The study's contributions are theoretical, methodological and practical. These contributions are briefly outlined in the following paragraphs.

1.7.1. Theoretical contributions

This research aims to present a juxtaposition of various commerce disciplines – financial accounting (preparation of financial information), finance (the consumption of financial information by investors) and economics (the economics of information). It then discusses and compares literature and methodologies within and across these disciplines in an attempt to demonstrate the common thread of uncertainty in the information environment.

The current study extends the existing research on integrated reporting (Atkins & Maroun, 2015) by solidifying the link to the use of this information and its ultimate impact on the market. This research fills a gap between the accounting and finance literature by exploring the potential influence of information-related factors on the analysts' forecasts. It combines aspects from the decision-making process of analysts and the rest of the market with the expected outcomes based on the information on company fundamentals that is produced. In so doing, it presents a theoretical contribution.

In a study on analysts in India, Chaudary, Sahoo and Dawar (2022) highlight the relevance of an emerging economy in this context as information flows and corporate governance requirements are different to capital markets in more developed countries. In light of this distinction, the South African context is particularly significant because JSE- listed companies are effectively required to produce Integrated Reports (Atkins & Maroun, 2015) which are intended to improve the information environment in the capital markets (IIRC, 2021). In fact, it was the first country to adopt mandatory integrated reporting via the King III Code of Conduct (Eccles *et al.,* 2019) despite its classification as an emerging economy.

In this research, integrated report quality would have been rated by the expert adjudicators in the EY Integrated Reporting awards. These ratings are awarded according to three categories, derived directly from the Integrated Reporting Framework (IIRC, 2021). The quality score data is therefore most similar to that used in Barth *et al.* (2017) and represents a more detailed view of report quality than studies which are limited to the rankings released from EY, on a scale of 1 to 5 (for example see, Mokabane & Du Toit, 2022).

Research on behavioural finance usually focuses on one behavioural factor (for example, Barber & Odean, 2001; Hilary & Menzly, 2006). However, the interactions and relationships between the biases may provide original insights. By considering the effects of several biases together, this research presents a theoretical contribution.

1.7.2. Methodological contributions

The research on analysts who follow South African companies is scant and dominated by empirical analyses of recommendation accuracy (for example, Ahmed & Flint, 2020). To the best of the researcher's knowledge, at the time of writing, this is the first study that includes a qualitative analysis of interview data solely from equity analysts in South Africa, which is considered a developing economy, with different levels of information asymmetry.

It is rare to find academic research which presents the views of equity analysts because of the difficulty in obtaining access to the analysts (Smith & Van Der Heijden, 2017). The present study details first-hand accounts of the drivers of the investment decision processes of these analysts and extends the research of Abhayawansa *et al.* (2019) by including the role of heuristics and bias in the formulation of forecasts. In doing so, this study responds to the concern about the stagnation of theory which comes from a lack of researcher-practitioner interaction (Coleman, 2014).

Imam and Spence (2016) provided a field study of buy and sell-side analysts. They selected analysts from the top 15 institutional investment firms from the Extel Survey website to interview. Extel Survey ranks analysts from European institutional investment firms, similar to the Financial Mail Analysts Awards in South Africa. To the best of the researcher's knowledge, this study is the first to present the views of sell-side equity analysts that cover JSE-listed companies. This context is interesting because South Africa is a developing economy, yet it has the nuance of integrated reporting being effectively mandatory for JSE-listed firms. The setting has the potential to lead to inferences about the usefulness of the integrated report, a significant development in corporate reporting (Atkins & Maroun, 2015; Eccles *et al.*, 2019), whilst also including the information environment of a developing economy, as in Chaudhury *et al.* (2022).

We use a mixed methods approach, thereby answering the call for supplementary approaches to explaining financial decisions and behaviour (Kearney & Liu, 2014; Dewasiri, Weerakoon & Azeez, 2018; Ahmad, 2020). The combination of qualitative and quantitative data allows the researcher to compare and contrast the results from the respective sources. In this manner, the paper makes a methodological contribution. With structural equation modelling (SEM), empirical data is modelled and fit-statistics are used to assess the model in relation to the data. If the fit is not acceptable, the modelled relationships will not be regarded as supported by the quantitative data. The qualitative data may then provide explanations for the lack of fit. Particularly, we have chosen SEM as it is used for the modelling of latent constructs which are common in the behavioural finance research (Smith and Langfield-Smith, 2004).

Measurement approximations that have been established in seminal integrated reporting literature are used in this research and their application is extended to empirical analysis by way of structural equation modelling. The use of structural equation modelling instead of the more commonly used regression models presents a methodological contribution to the existing integrated reporting literature. We propose analysis using structural equation modelling instead of a regression (for example, as in Barth *et al.*, 2017). SEM is superior to a regression analysis as it considers several equations simultaneously. A single variable may be a predictor in one equation, and it may be a criterion in another equation. In particular, for this study, SEM allows integrated reporting quality to be treated as a latent construct instead of a directly observable variable. This latent variable is measured using various indicator variables. The deconstruction of the latent quality variable into several observable indicator variables lends itself to an extended analysis on the relationships between the quality indicator variables and the information asymmetry indicator variables. To this end, the researcher exploited SEM's strength of capturing relationships between latent variables such as the directly unobservable quality indicator. SEM therefore allowed us to make inferences about the impact of each of the separate aspects of information quality on information asymmetries.

1.7.3. Practical contributions

The present research comes at a time when there is likely to be scepticism about the quality of information, possibly due to recent corporate governance and auditing failures. The research did not seek to determine whether investor reaction is justified, nor did it aim to suggest remedies for the recent audit failures. Consistent with the pragmatic worldview that it adopted (Creswell & Creswell, 2017), the research sought to understand the *resultant* cognitive and emotional biases that may impact the capital markets. Ultimately, it seeks to make a practical contribution by identifying possible contexts in which biases are likely to influence market behaviour.

1.8. Chapter Conclusion

This chapter provided the foundation for the rest of this inter-disciplinary study. The focus of the study was established as the use of integrated reports by sell-side equity analysts and its potential influence on their proclivity for behavioural bias. This focus area underpins the research questions, which were also introduced in the chapter. Additionally, the primary theoretical frameworks that underpin each aspect of the study were introduced, as depicted in Figure 1. Finally, the anticipated contributions of the study, both to the related literature as well as practical applications, were introduced. Chapter 2 details the related prior literature and develops hypotheses to test the research questions.

Chapter 2: Literature review and hypothesis development

2.1. Introduction

A review of the literature is especially important for this interdisciplinary study. Various strands of relevant research must be aligned to the common theoretical framework of the information environment to enable a cohesive scientific enquiry.

Commencing with a detailed exploration of the information environment, the chapter contextualises subsequent sections. These sections are organised according to the study's three research objectives. Given that the first research objective relates to the production of new information, initial focus is on the literature pertaining to corporate reporting. The absorption and use of this information is the focus of the second and third research objectives. Therefore, in the second part of the literature review, attention shifts to the role of equity analysts in the information environment. The third research objective entails an examination of the effect of behavioural bias in the context of analysts. Consequently, the third part of the literature review details the behavioural finance literature on analysts' behavioural biases. In each of these three sections of the chapter, hypotheses are developed for testing in the study. In this sense, the use of prior literature and relevant theories is important because the quantitative analysis includes structural equation modelling, which tests a theory by specifying a model that represents predictions of that theory as it relates to constructs.

The latter sections of the chapter concentrate on the methodologies used in the pertinent literature. The methodologies are compared and evaluated, with specific focus on the complexities of the quantification of behavioural bias. Each section of the literature review culminates in an identification of gaps in the existing literature. These gaps are categorised according to each of the three research objectives and considering their collective implications.

2.2. Uncertainty and the information environment

The term "uncertain" is defined in the Oxford English Dictionary as "being indeterminate as to magnitude or value". The state of being uncertain, that is, uncertainty, has been extensively researched in the context of economics, psychology and accountancy.

Perhaps the most commonly used seminal work on behavioural economics and behavioural finance (Kahneman & Tversky, 1974) is titled "Judgement under *uncertainty*: Heuristics and biases" (emphasis added). The use of heuristics was shown to be more likely in situations of uncertainty, where a subjective assessment of quantities is required. Uncertainty, in this context, arises from incomplete information that is required to predict future performance of companies' shares. In order to minimise this uncertainty, corporate financial reports aim to provide information that is useful to the providers of capital.

The "information environment" refers to the overall context or ecosystem in which information about a company is created, disseminated, and processed (Healy & Palepu, 2001; Blankespoor, Miller & White, 2014; Kim, Ryu & Yang, 2021). It encompasses the various sources, channels, and methods through which information is generated, communicated, and received by stakeholders, including investors and analysts. The information about the firm includes both financial and non-financial information, such as SENS announcements, integrated reports and result presentations. Disclosure of this information can be either voluntary or required by regulation. A company's information environment has an impact on the functioning of financial markets. A poor information environment can reduce informational efficiency and lead to a higher cost of capital (and a lower firm value) (Barth *et al.*, 2017).

However, investors can be influenced by deficiencies in the information environment (as they consume information), as well as their own biases. Tversky and Kahneman (1974), in their research on decision making under uncertainty, explain how sub-optimal decisions can be made when individuals use heuristics. The heuristics discussed in this seminal research result from the cognitive limitations of the mind. There is a plethora of research on the biases of equity analysts (see, for example, Bernhardt, Campello & Kutsoati, 2006; Hilary & Menzly, 2006; Hirshleifer, Lourie, Ruchti, & Truong, 2020). Research on the biases of analysts appears to affirm the link between uncertainty and behavioural bias (Zhang, 2006). For example, analysts display higher levels of biases when producing forecasts for firms that are more complex to value such as those that have high levels of research and development expenditure or intangible assets (Daniel, Hirshhleifer & Subramanyam, 1998; Bassiere & Elkemali, 2014).

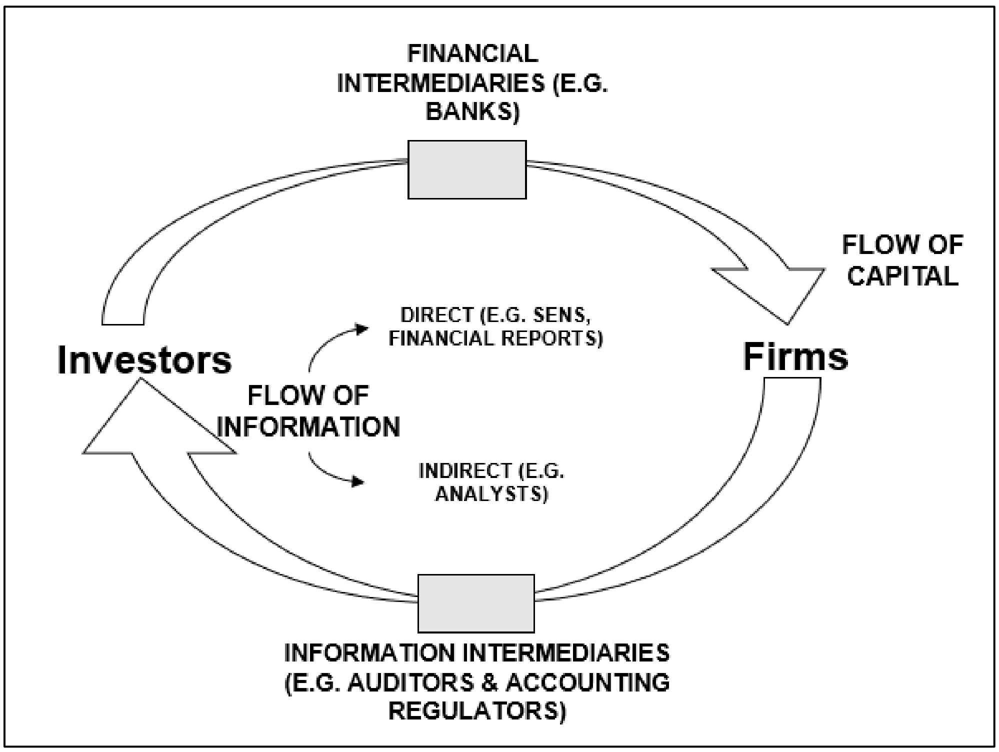
Whilst the uncertainty-bias link appears affirmed in prior studies, findings of the precise causes and impacts of the uncertainty on forecasts has been varied. Zhang (2006) postulated that uncertainty could arise from a volatility in the firm's fundamentals and/ or poor information. The author hypothesised that if analysts under-react to new information when revising their forecasts, this underreaction will be more pronounced when there is greater uncertainty. In support thereof, the author found that greater information uncertainty is associated with more positive forecast errors and subsequent revisions, following the release of bad news. The converse was observed for good news. In the context of specific biases, similar evidence was provided by Baessiere and Elkemali (2014). The study showed that analysts are more prone to the overconfidence bias in situations of greater uncertainty. In somewhat contrarian findings, Song, Kim and Won (2009) showed that analysts display lower levels of the herding bias when there is more uncertainty in the information environment. The authors posit that this is a result of a greater incentive for the analyst to provide new information to the market and therefore differentiate themselves from their peers.

Healy and Palepu's (2001) depiction of financial and informational flows illustrates key role players in the information environment of a firm. This depiction is adapted in Figure 2. Information is shown as flowing from firms to investors, often via information intermediaries and/ or financial intermediaries. It is therefore unsurprising that the literature that examines the manner in which firms communicate this information is as vast as the literature that focuses on the manner in which information is received by investors.

In a reflection on prior seminal literature on "accounting communication", Lee (1982) observes that accounting has been presented as a series of measurement activities although it can also be seen as the communication of a series of signals that are transmitted by the firm. Extending this line of research, Brennan and Merkl-Davies (2018) used the concept of connectivity from the communication studies literature to evaluate how effectively firms communicate to their investors in the capital markets. Their framework identifies, amongst others, how and to whom, information is communicated. A firm can communicate in writing, orally, or even send a signal by being silent. The authors identify the communication medium as an area for future research focus, especially as firms expand their digital presence. For example, Blankespoor, Miller and White (2014) found that dissemination of corporate information via Twitter is associated with lower abnormal bid-ask spreads, indicative of a reduction in information asymmetry.

The research by Brennan and Merkl-Davies (2018) and Blankespoor *et al.* (2014) illustrate that it is not only the content of any one form of corporate report that influences the allocation of investment in the market. Instead, it is a combination of the content, media and intention of the communication and the communication providers that combine to form the information environment in the capital market.

Figure 2: The information environment



Source: Healy and Palepu (2001), Adapted.

Information intermediaries include auditors, accounting standard setters, regulators and analysts (Healy & Palepu, 2001, Barth & Hutton, 2000). The information contained in corporate reports can be perceived as a public good – the company's current investors pay for its production indirectly, but they cannot charge potential investors or stakeholders for their use of the information (Watts & Zimmerman, 1986). In this context, regulation is required to ensure that firms provide necessary and relevant information for economic decision-making.

Accounting standards serve to reduce processing costs for users of financial statements by providing a universally accepted language that managers can use to convey information to investors and other stakeholders. However, there has been debate about the role of accounting information. Some researchers opine that the primary objective of accounting reports is to provide historical information that enables the holding of management to account. Other researchers prioritise the provision of information that is value relevant to investors in the market. Whilst these two objectives are not always mutually exclusive, the International Financial Reporting Council appears to have favoured the provision of information to the market to reduce the uncertainty that arises when managers have more information than owners or potential owners (IIRC, 2021).

Auditors provide users of the financial statements with independent assurance that the information is free of material misstatement. In this manner, they seek to enhance the credibility of reported financial information (Healy & Palepu, 2001). Analysts have also been shown to play an external monitoring role, thereby enhancing the information environment. Chen, Xie and Zhang (2016) showed that high quality forecasts were associated with more efficient internal investment decisions. These effects were stronger for firms with higher information asymmetry. Barth and Hutton (2004) found that the share prices of firms with higher analyst coverage more rapidly incorporated accounting information on accruals than less followed firms. This suggests that they provide an oversight role, similar to that of the regulators, albeit less independent (see Section 2.12.1. on analysts' incentives).

Analysts further contribute to the information environment by providing new information and interpreting previously released information. They use the information provided by firms, along with direct interactions with management, to make forecasts about the future prospects of the firm. Their reports typically include recommendations of whether investors should buy, hold or sell a stock. These research reports play a key role in improving the information environment of a firm. For example, Piotroski and Roulstone (2004) found that analyst following leads to greater synchronisation of a firm's stock returns to the returns of the rest of the market. The results of their study suggest that analysts make two key contributions to the information environment. Firstly, they gather and disseminate firm-specific information to the rest of the market. Secondly, they identify relevant portions of market information and disseminate it to investors. These gathering and processing activities of analysts enhance the information environment as they result in firm specific returns being driven less by noise trading and more by new, relevant information (Kirk, 2011; Imam & Spence, 2016).

The investor relations function is pivotal to the facilitation of information transfer between the firm and its investors and other stakeholders, thereby contributing to the reduction of uncertainty. Their role is not separately identified in Figure 2 from Haley and Palepu (2001), possibly because their function has been viewed as more relevant to "corporate public relations" (Laskin, 2011 p.303) than to corporate reporting. A key component of their role is to establish and build relationships with company stakeholders, including analysts. Nel and van der Spuy (2021) provide one of the few academic works that describe investor relations practices in South Africa. They find that the information needs of institutional investors are most important to investor relations practitioners. Interestingly, the informational needs of sell-side analysts ranked below those of existing institutional investors, buy-side analysts and prospective institutional investors.

Another reason for the absence of the investor relations function from Figure 2 is possibly because the importance of the investor relations function to the company's cost of capital has been acknowledged relatively recently (Laskin, 2011), more so in the South African context (Nel, Smit & Brummer, 2018). The latter study, whose focus was entirely on internet investor relations, employed a content analysis of investor relations websites. Findings indicated that the quality of internet investor relations was significantly negatively related to the company's cost of debt.

The focus of other research efforts in the South African context have been on the use of the internet (Nel, Smit & Brummer, 2018) and social media platforms as a contribution to the investor relations function. Esterhuyse (2018) identifies the link between the investor relations function and the work of analysts. Using regulations which govern disclosure as the underpinning of the study, the author examined the extent to which companies' investor relations functions published analyst recordings and presentations on their websites. The study found that analysts who are present at the results presentations and roadshows are afforded an informational advantage because companies do not provide audio or visual recordings of the presentations.

It is evident that in the context of the information environment, there are various reasons for and implications of uncertainty. As espoused in agency theory, uncertainty arises because of the absence of information. According to theories on judgement and decision-making, this absence of information has implications for the cognitive processes of analysts.

2.3. The usefulness of corporate reports

Developments in Integrated Reporting have been hailed as an important step in enabling the efficient allocation of resources in capital markets. Chaudhury, Sahoo and Dawar (2022) studied the interaction of sell-side and buy-side equity analysts in India. A key motivation for the study was that India is an emerging market where the dissemination of information and corporate governance standards are different from those in developed countries. In these contexts, JSE-listed companies can be regarded as pioneers with their mandatory publication of integrated reports. Yet, the forecast accuracy of analysts of JSE-listed companies is scant, especially with regards to the analysts' use of corporate reports.

Whilst its primary intended users are providers of capital, its benefits appear to extend to internal investment decisions. Barth *et al.* (2017) found a positive relationship between integrated report quality and firm value, measured using Tobin's Q. Furthermore, firms with greater integrated reporting quality were found to have lower bid-ask spreads. Similarly, Zhou *et al.* (2017) found that alignment to the Integrated Reporting Framework was aligned to a reduction in analyst forecast dispersion. These findings are in line with the proposition that investors are willing to accept a lower rate of return as a result of reduced information risk from the improved information environment. Zhou *et al.* (2017) acknowledge the potential benefits of an integrated report in the context of cognitive limitations and information processing abilities of analysts with regards to complicated financial information. The researchers suggest that even if an integrated report is an improved formatting of information currently provided, it could still beneficially impact upon users' information processing. This is because the importance of salient non-financial information will be highlighted. However, all these potential benefits are not unequivocal.

Barth *et al.* (2017) found no significant association between integrated report quality and analyst forecast accuracy. Pistoni *et al.* (2018) found the quality of integrated reports to be low as they lacked important forward-looking information. They also found that there was an insignificant improvement in the quality of reports from one reporting period to the next. It appears that findings on the relationship between internal reporting and forecast accuracy or firm value tend to differ based on the items and scale used to quantify quality.

Whilst most measurement approximations are based on the Framework provided by the IIRC, there are variations in the specific attributes of quality. Barth *et al.* (2017) uses data from audit firm EY, which rates the quality of integrated reports of the largest firms on the JSE. Pistoni *et al.* (2018) used an adapted scoreboard from Hammond and Miles (2004). Eccles *et al.* (2019) used a scale based on the Integrated Reporting Framework but also included input from investor letters. Amongst these empirical studies, there are also differences in the choice and measurement of the control variables and dependent variables. For example, Barth *et al.* (2017) use, as an approximation for firm value, Tobin's Q, which has been criticised for being subject to considerable measurement error (Perfect & Wiles, 1994). In addition, the studies are subject to a limitation on replicability due to the subjective nature of the coding of the quality variable.

Even if the issues of reliability of measurement approximations are cast aside as being overly pedantic, there is still uncertainty regarding the benefits of producing integrated reports. Haji and Anifowose (2016) highlight impression management as a key driver of information disclosed. They find that whilst the quality of information has improved over time, integrated reporting practice is largely ceremonial in nature. As evidence, the researchers cite the incorrect application of commonly used integrated reporting terms such as "increase" and "decrease". They find disclosures are made as "symbolic gestures", in keeping with the finding of a check-box approach to reporting (Atkins & Maroun, 2015). Cerbone and Maroun (2020) call for further research on how to report multiple types of capital to enhance the usefulness of disclosed information. They explain that the competing stakeholder and market perspectives can result in fundamental differences in information that is emphasised. The diverse evidence on an important component of information produced by companies provides the initial indication of remnants of uncertainty and information asymmetry in the market. The market implications of integrated report quality are examined in this study, using the following hypotheses:

> H1.a. The quality of information contained in a company's integrated reports has a positive relationship with the quality of analysts' forecasts for that company.

> H1.b. The quality of information in a company's integrated reports has a positive relationship with share price performance of that company.

2.4. Quality of integrated reports

"Quality" is an inherently subjective and context-specific construct. In the context of the integrated reports; Cerbone and Maroun (2020) explain that the evaluation of integrated reports against pre-determined standards (or auditing them) is challenging as it contains narratives, qualitative information and estimates. Prior research on the production and use of integrated reports uses a variety of methods to determine quality. Qualitative studies such as Atkins and Maroun (2015) use interpretive thematic analysis to synthesise the quality criteria that institutional investors use for integrated reports. Similarly, Abhayawansa, Elijido-Ten and Dumay (2019) conduct interviews with analysts to evaluate the extent of their use of integrated reports. In so doing, they gauge the quality of integrated reports by the extent to which they fulfil their purpose of providing suitable information to investors. Quantitative researchers have used quality scores, generated through a process of content analysis and coding (Haji & Anifowose, 2016; Pistoni *et al*., 2018; Eccles *et al*., 2019).

EY, a big four audit firm, conducts annual reviews of integrated reports for their "Excellence in Integrated Reporting" awards. These awards are intended to provide benchmark standards of quality in integrated reporting to companies' stakeholders. The top 100 JSE-listed companies by market capitalisation on 31 December each year are considered for the awards. In order to arrive at the scores, the reports are evaluated against the recommendations of the International Integrated Reporting Framework. These recommendations are broadly grouped as "guiding principles" and "content elements", with "fundamental concepts" as the basis of the guidelines (IIRC, 2021).

The fundamental concepts of an integrated report are the capitals (IIRC, 2021). These capitals are resources that are consumed or transformed during the creation of a company's product or service. They are classified as financial, manufactured, intellectual, human, social and relationship and natural capitals. According to the framework, integrated reports should include information on the impact of the company's operations on these capitals.

The information in the integrated report should be underpinned by guiding principles which inform how the content is presented. These guiding principles include future orientation and reliability. In addition, any integrated report should include eight content elements, including company performance and outlook. An extract from the International Integrated Reporting Framework which details the Guiding Principles and the Content elements is presented in Appendix A.

2.5. Integrated thinking

According to the International Integrated Reporting Council (IIRC, 2021), in addition to the aim of providing information to the providers of financial capital, integrated reporting is also intended to support integrated thinking and decision-making within the firm so that sustainable value is created. The concept of integrated thinking has been explored in relatively recent research endeavours. Whist integrated reporting deals with external corporate reporting, integrated thinking focuses more on the decision-making processes within an organisation. Integrated thinking refers to consideration by an organisation of the relationships between its various internal functions and the types of capitals that the organisation uses for the creation of value (IIRC, 2021). This notion of cross-functional collaboration within the organisation, is similar to the most recent versions of the balanced scorecard (Dimes & de Villiers, 2023).

Ecim and Maroun (2023) performed a comprehensive bibliometric analysis of the integrated thinking literature. Their trend analysis showed that the South African market provided a rich context for integrated reporting studies, although research interest in the topic has waned with

South Africa ranking joint third with Australia in terms of research output. The authors posit that this trend may be a result of South African universities prioritising professional training over research. In this study, we proffer an additional or alternative explanation – the research interest in integrated thinking may be low due to repeated findings of the lack of impact of integrated reports on the capital markets (Rensburg & Botha, 2014; Willows & Rockey, 2018; Mokabane & du Toit, 2022). The alternative explanation may also be relevant to the observed low interest in integrated reporting (to which integrated thinking is mentioned as concomitant, in Dimes and de Villiers, 2023) from other emerging economies. One cannot ignore the possibility that researchers in these countries see little value in integrated reporting and therefore direct scarce resources to what are perceived as more pressing issues. The priorities may shift as the benefits (if any) of integrated thinking are explored and documented and integrated thinking is established as a mechanism of creation of value instead of a concomitant to integrated reporting.

Integrated thinking is strongly associated with integrated reporting (Dimes & de Villiers, 2023). The IIRC asserts that the adoption of integrated reporting can lead to improved decision-making, by encouraging collaboration between different areas of the business (IIRC, 2021). In this way, the business will respond to the needs of various stakeholders, thereby fostering sustainable value creation. Yet, there is evidence that integrated thinking can exist independently of integrated reporting. Collaborative management practices may be promoted by the adoption of integrated reporting but can also exist without it (Dimes & de Villiers, 2023). This notion of correlation and not causation (Pearl & Mackenzie, 2019) makes it challenging for researchers to establish the effect of integrated reporting on integrated thinking.

2.6. Audit failures

Aside from variations in the quality of information produced by companies, the information is only useful if it can be relied upon. Debates on the quality of Integrated Reports have predated this research and may likely continue into the future, as many countries grapple with the complexities of the adoption of the IIRC's recommendations. Similarly, recent follies in the accounting profession may precipitate further research on the limitations of audits (often referred to as the *expectation gap* or discussed as *materiality*) and on ethics in the accounting profession. Preparers, who are internal to the firm, are expected to produce correct information as the compliance with internationally recognised accounting standards is independently verified by external auditors. In his tracing of information economics through centuries of economic theory, Stiglitz (2000) cites costly state verification. If the financial information of companies cannot be audited, then they must be verified by the state, making information more expensive and restricting the use of equity. Whilst this example may be far-fetched for current circumstances, it contributes to the argument that failures in audit processes can lead to a reduction in equity market participation or, at least an increase in the cost of equity.

Regardless of the outcome of important deliberations on report quality and the audit profession, recent corporate failures, despite the abundance of oversight mechanisms has cast doubt in the minds of consumers of financial information (Rossouw & Styan, 2019; Visser, 2019; Crotty, 2020). These ideas have also been explored in research on trust in capital markets. In attempting to explain factors that influence stock market participation, Guiso, Sapienza, and

Zingales (2008) find that investors consider the risk of being cheated before they invest in the stock market. They explain that events, such as the collapse of Enron fundamentally alter the perception of fairness in the stock market. Whilst these episodes may be relatively uncommon, the authors explain that the perception of market participants is a function of both objective and subjective beliefs. This is because it is difficult to estimate the true probability of a very rare event. The empirical findings show that lack of trust is a significant factor that influences stock market participation with lower levels of trust linked to lower levels of participation. Rahman (2019) explains that trust is necessary before investors take the risk of equity investments. They find that trust significantly impacts the decision-making process. It reduces stock market participation although at a lower level of significance for more informed and educated investors. The uncertainty may result in adverse selection in relation to financial information.

In the seminal work on adverse selection, Akerlof (1978) acknowledges that there is an economic cost for dishonesty and proposes a framework for determining this cost. In the study, the researcher uses an analogy of employers who do not employ candidates from establishments that are not credible, despite the possibility of worthy candidates from those establishments. For the employer, this is the result of being unable to distinguish candidates with good qualifications from those with bad qualifications. The researcher also explains adverse selection using used cars or "lemons" where poor quality products drive out the good products. Stiglitz (2000) furthers the discussion on adverse selection in the context of borrowers and lenders. As a result of information asymmetry, lenders raise interest rates to compensate for possible additional risks. As an unintended consequence, the best borrowers leave the market. The idea of adverse selection may be extended to the equity capital markets; if markets participants are doubtful of the information they are receiving from the firm, they may not trade its shares, or possibly shares of similar firms. The receivers of information – say, regarding a security - will offer a price that accounts for the possibility that the information may be flawed rather than a price that reflects the true value of the security.

These ideas are extended in the works on ambiguity aversion. Heath and Tversky (1991) offer ambiguity aversion as a possible explanation for why low-knowledge bets are less attractive than high knowledge bets. Individuals prefer contexts in which they perceive themselves as relatively well-informed. If investors perceive a higher probability of imperfect information, they may be reluctant to diversify their portfolios based on accounting information of firms with which they are less familiar. They may tend to rely on a small number of firms with whose operations and financial positions they are more familiar (Heath & Tversky, 1991).

Schneier (2008) explains that perceived security (or conversely, perceived risk) is influenced by empirical evidence as well the as individual's emotions. The researcher attributes the divergence between the reality and feeling to behavioural bias. According to research regarding the amygdala and neocortex in the field of neuroscience, it is likely that where the reality and perception of risk are at odds, the perception of risk will triumph. As an example, Schneier (2008) describes a man who survives a possibly fatal accident involving a poorly-installed window during a violent storm. The survivor explains that even though the window has subsequently been fixed and he "know[s] these facts", the sound of fierce winds still causes his adrenaline to rise. This is despite the rational belief that he is safe. Therefore, the reality of whether prepared financial information is correct is largely irrelevant if the perception is different.

Rothschild and Stiglitz (1978) examined the implications of imperfect information on a competitive market, using the insurance market as an example. They conclude that institutions within markets may have been established as a manner of handling problems with information. An example of such an institution may be the external audit firm whose purpose is to assure users of financial statements that these are free from material error. However, the level of comfort provided by auditors to consumers of information is likely to have been significantly impacted by recent instances of audit failure. The lack of trust in the audit process is closely related to the discussion in the section on audit failure in this proposal. Rahman (2019) explains that trust is necessary before investors take the risk of equity investments. They find that trust significantly impacts the decision-making process.

2.7. Knowledge gap

The international research on investor relations is well established (Hoffmann, Tietz & Hammann, 2018) and includes studies which provide empirical evidence of its value (for example, Laskin, 2011). The South African investor relations literature has identified the investor relations function as a means to reduce information asymmetry and has also provided initial evidence of the impact on a company's cost of capital (Nel, Smit & Brummer 2018; Nel & van der Spuy, 2021). The focus of the South African research has however, been on the role of internet investor relations. This is presumably due to ease of access to data that serves as an approximation of the quality of investor relations (see for example, Nel *et al.*, 2018). There appears to be a paucity of research that investigates the dynamics of investor-company interaction in investor roadshows and presentations. For example, Salzedo, Young and El-Haj (2018) studied the analysts' notes and conference call questions for evidence of rigour and objectivity on the part of the analysts. This type of analysis of the direct communications between management and investors appears to be lacking from current investor relations research endeavours. This gap in research becomes more glaring, given the findings of Esterhuyse (2018) that firms rarely publish records of proceedings of analyst presentations and investor roadshows.

Preparers of financial information do not always produce information that is entirely correct, either intentionally or unintentionally. Prior literature shows that investors appear to have learned to protect themselves from apparently poor-quality accounting information, as market participants do in theories of adverse selection (Akerlof, 1978). There appears to be a gap in the research that examines biases as a result of information that is perceived to be incorrect as a result of potential manipulations that have gone undetected by external reviewers. This research aims to fill the gap by extending the literature on investor scepticism in an examination of concomitant behavioural biases.

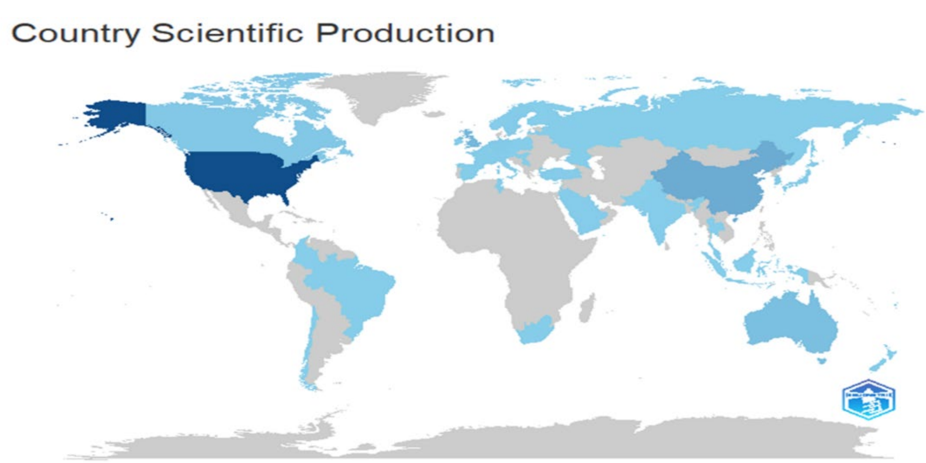
2.8. A "big picture" view of research on sell-side equity analysts

For this study, it was necessary to obtain a high-level overview of the research on equity analysts. To this end, the researcher employed bibliometric analysis. Bibliometric analysis allows the scanning of metadata relating to large volumes of academic literature. In doing so, the tool provides a "big picture" view of trends and themes in a particular research area (Aria & Cuccurullo, 2017). For this study, bibliometric data was analysed using Biblioshiny version 3.1.4. Biblioshiny is an internet-based application from the Bibliometrix package that was created by Aria and Cuccurullo (2017) in the R programming language. Biblioshiny is an open-source tool that is frequently upgraded and integrates easily with other statistical R-packages. It is compatible with various online bibliographic databases, unlike other bibliometric packages in the R environment. Another reason for the choice of Biblioshiny in this study, is the tool's functionality relating to co-citations, co-word analysis and the extraction of specific text from article titles and abstracts (Joshipura & Wats, 2023).

Metadata was collected from the online bibliographic database, Clarivate Analytics Web of Science (WOS) database. The database provides comprehensive coverage of articles in the management and finance fields, and therefore contains works from highly-rated journals and established authors. In total, the WOS database has over 75 million records (Joshipura & Wats, 2023).

The researcher searched for "analyst recommendations" and "sell-side analysts" as topics. The document type was set as "articles" and a time period of 33 years to 2023 was chosen. This time period was chosen to coincide with a period aligned to South Africa's financial liberalisation as the present study focuses on the South African market. The data was scanned for duplicates or irrelevant material. Finally, a total of 414 articles, across 99 journals were used in the analysis. A list of the journals contributing more than three articles to the analysis is provided in Appendix M. The journals focus on accounting and finance research, suggesting that the studies focused on the common ground of these two disciplines – the information environment. The majority of articles (27) featured in the Accounting Review, with the Journal of Behavioural Finance featuring nine articles. Prominent journals include the Journal of Accounting & Economics and the Journal of Financial Economics. Journals focusing on emerging economies (Journal of Accounting in Emerging Economies and International Journal of Emerging Markets) contained one publication each, both in 2023. Figure 3 shows scientific production by country. The United Sates of America is featured most frequently in articles (frequency of 722), China with a frequency of 179, South Africa with a frequency of eight and Brazil and India with frequencies of six and ten respectively.

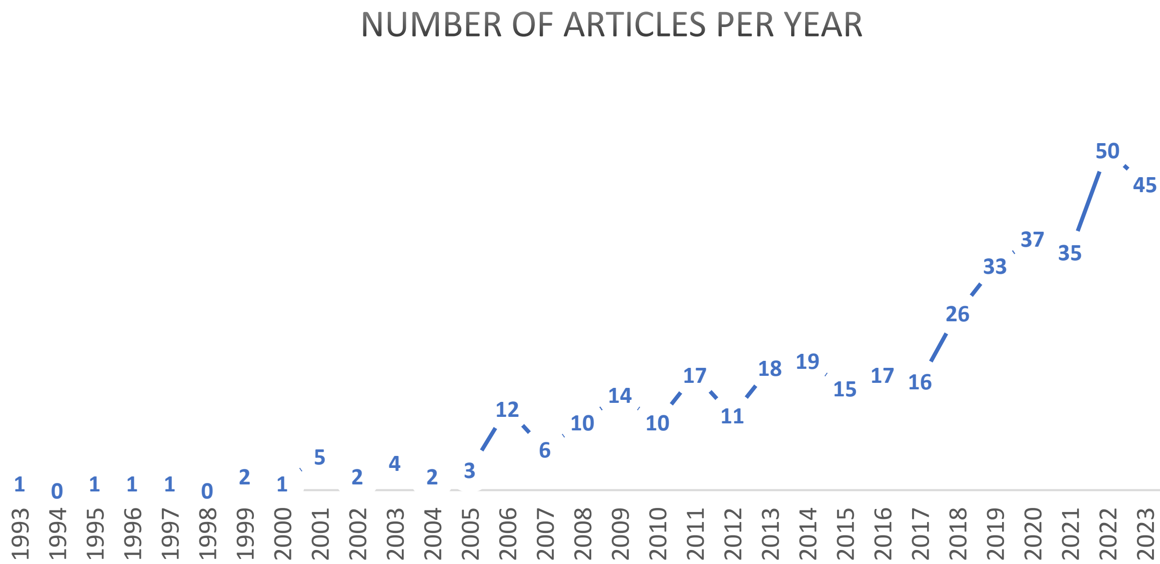
Figure 3: Research frequency by country



Source: Biblioshiny (2023)

The graph of annual production in Figure 4 shows an upward trend in the number of articles per year. Overall, there appears to be growing research interest pertaining to equity analysts.

Figure 4: Annual Scientific Production



Source: Author's compilation from Biblioshiny

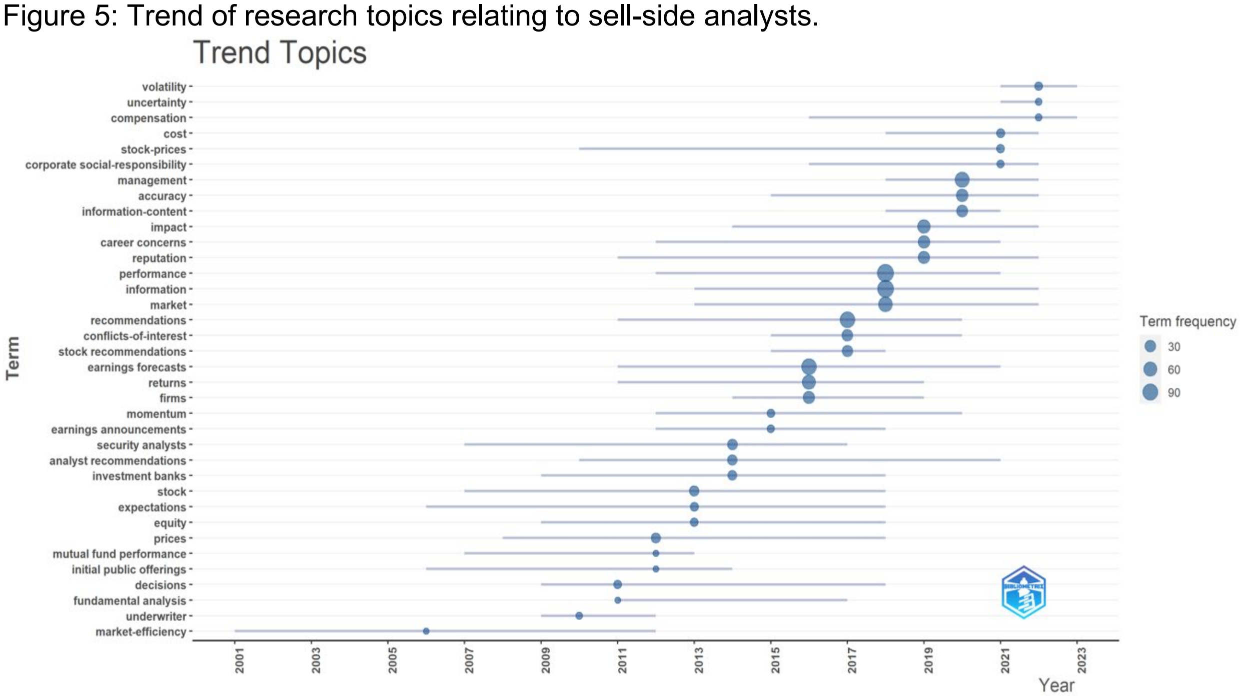
Further analysis of the bibliometric data showed that the most cited author in the selected time period is Lawrence D. Brown. The paper (Brown, Call, Clement & Sharp, 2015) titled "Inside the 'black box' of sell-side financial analysts" in the Journal of Accounting Research, had 1125 citations at the time of writing. The term "black box" refers to relatively unexplored aspects of the analysts' decision processes and the use of their recommendations by the market. It was a notable study at the time as it was one of the few that provided insights from direct interactions with analysts using a survey (365 responses) and follow-up interviews (18 participants). This direct interaction allowed the researchers to gain insights that would be difficult to obtain from ex-post trading data and recommendations. Specifically, the study explored the inputs analysts use and the criteria against which their competence is evaluated. It focused on analysts who covered U.S firms in 2012. The study's key finding is that analysts considered private communication with management to be more useful than their own research and reports of financial performance.

Figure 5 shows that the research on sell-side analysts has focused on market efficiency in the earlier 2000's, conflicts of interest between 2015 and 2017 and corporate social responsibility, in the earlier parts of the current decade. Early research on sell-side analysts was dominated by empirical analyses of the accuracy of their forecasts. However, following the highly cited work of Asquith *et al.* (2005) titled "Context, not predictions", research focus shifted to analysts' incentives. Analysts' incentives and potential conflicts of interest attracted peak research attention between 2015 and 2017. This followed a steady increase in the research on analysts' conflicts of interest, precipitated by the Global Analyst Settlement Agreement of 2003, which dealt with the incentivisation of sell-side analysts in large banks and brokerage houses[3].

Expectedly, research on uncertainty and volatility coincide and were dominant as the global economy was reeling from the unprecedented effects of the COVID-19 pandemic and associated lockdowns. Notably, it appears that the information environment is a common theme across the years, with terms such as "market efficiency", "information", "information content" and "uncertainty" featuring consistently from the early 2000's. The results from the bibliometric analysis also reveal that "information" is the second most relevant word in the metadata, with a frequency of 109[4].

The seminal work of Asquith *et al.* (2005) was the most cited article in relation to analysts. The study focused on the information contained in equity analysts' reports. It was one of the first studies that extended the research focus beyond the recommendation and price forecasts. They examined the entire text of the analyst report, including aspects such as valuation methodologies and how the analyst justified their recommendation. Their study made a novel contribution by quantifying certain qualitative aspects – for example, they created a "strength of arguments" variable (p.246), for subsequent use in a regression analysis. Another highly cited study, Merkley, Michaely and Pacelli (2017) focused on "optimism bias" (p.1288), which arises from the incentive of greater investment banking fee revenue. This focus is notable as the study was published several years after the seminal work of Hong and Kubic (2003) on incentive conflicts, **and** after the Global Analyst Research Settlement Agreement of 2003 (further discussed in Section 2.12.1.). This suggests that the issue of incentive conflicts continues to attract research attention even after the regulatory steps taken by the SEC.

Figure 5: Trend of research topics relating to sell-side analysts.



[3] Further detail on the Agreement is provided in Section 2.12.1. of this study.
[4] The word "performance" is the most relevant word, with a frequency of 114.

Source: Biblioshiny (2023)

Since the focus of this study is on behavioural biases of analysts, the author further refined the search to include the term "bias". The results of the bibliometric analysis pertaining to biases are presented and evaluated in the section titled, "Approaches to the quantification of bias" in Section 2.14.3. of this study.

2.9. Sell-side equity analysts in the equity capital markets

Chen, Xie and Zhang (2017) classify analysts' roles according to three theoretical frameworks. Firstly, analysts are classified as information intermediaries as in several other studies (Asquith *et al.*, 2005; Kirk, 2011; Imam & Spence, 2016; Chaudhury *et al.*, 2022). They provide information to the market in the form of their recommendations and research reports. As such, they are intermediaries between the firm and its investors. To provide research reports and forecasts, the analysts must interpret the information provided in accounting statements and consider the context within which firms operate. In an exploration of information asymmetry in the capital markets, Healy and Palepu (2001) explain that analysts' forecasts and recommendations provide information to the markets that is new and in addition to the information contained in corporate reports. Similarly, Barth and Hutton (2004) found that analysts' use of information from a variety of sources enabled them to extend the disclosure provided in corporate financial reports. Specifically, they found that forecast revisions contain information about accruals and earnings persistence beyond what is reflected in most recent financial statements.

The second role classification provided by Chen *et al.* (2017) is the monitoring agent role. The idea of analyst monitoring was identified in the seminal work of Jensen and Meckling (1976). They assert that analysts have an advantage by their proximity to management and can thus reduce agency costs. In order to develop forecasts and produce research reports, analysts usually interface directly with management in results presentations, meetings or conference calls. This allows analysts to directly monitor (and possibly influence) management's decision-making. Consequently, analyst reports that contain discussions on corporate governance is a key mechanism through which analysts are able to monitor senior management and influence governance practices (Bradley, Gokkaya & Liu, 2017).

The third role classification from Chen *et al.* (2017) is the market pressure role. By publishing their earnings and price forecasts, analysts could indirectly create targets for management to achieve. This type of target-setting promotes disciplined investment decisions by management.

The remainder of this section focuses on these analyst roles in the information environment. Consistent with the "information intermediary" function, we structure the section according to the consumption of information and purveying of information by the analysts. This perspective is apt for this study which examines the effect on the information environment of the quality of company reports and how they are used by analysts to produce recommendations.

2.9.1. Analysts as consumers of information

Prior research has described the information processing role of analysts as an important part of the efficient functioning of the markets. They help investors make more informed decisions by interpreting financial accounting information and company fundamentals in the context of economic conditions and then disseminating this information into the capital markets (Imam & Spence, 2016; Du & Budescu, 2018). The information requirements of financial analysts therefore provide an interesting perspective in the integrated reporting literature as they are considered to be sophisticated users of information. They are therefore more likely to use the fundamental information provided in the corporate reports, making their work an attractive area of research in the finance academic community (Asquith *et al.*, 2005; Imam & Spence, 2016; Ahmed & Flint, 2020).

Analyst coverage also has the potential to reduce agency costs by providing a monitoring role. This monitoring effect is achieved directly by the analysts' constant and regular tracking of the financial statements and their interaction with management by raising questions in analyst presentations and conference calls. Although analysts do not intentionally focus on detecting fraud or intentional misreporting, the process of generating a forecast lends itself to an evaluation of earnings quality (Brown, Call, Clement & Sharp, 2015). Analysts are an important source of information for their clients and if their assessments of a company's performance are incorrect, the clients incur losses and the analysts' reputations are damaged. In contrast, the incentives of CFO's are commonly linked to share prices and firm performance. Therefore, analysts' views on the quality of financial information are considered by investors to be relatively unbiased and reliable (Brown *et al.*,2015).

Analysts also have information advantages as they are likely to have direct contact with management in results presentations, conference calls and meetings. In fact, so important is the direct communication with management, that analysts surveyed by Brown *et al.* (2015) reported having direct contact with either CFO's or CEO's at least five times a year. They can therefore provide indirect monitoring by disseminating public and private information to investors, thereby helping to detect poor corporate governance practices. For example, analysts were referenced as the second most common source of information in media reports of corporate fraud. The reporters themselves were the most common source of information (Miller, 2006). Consistent findings were produced by Brown *et al.* (2015) – coverage by analysts was associated with reduced earnings management and less CEO compensation. Furthermore, underperforming CEO's were found to be more likely to step down as the coverage of their firms increased.

Chen, Harford and Lin (2015) explored the monitoring effect of analyst coverage. They found that for firms with higher analyst following, the CEO's received less excess compensation and management made better internal investment decisions. Similarly, Chen, Xie and Zhang (2017) found that high quality earnings forecasts were associated with more efficient investments within the firm. These effects were stronger for firms with higher levels of information asymmetry. These findings suggest that financial analysts play an important role in monitoring management behaviour and that a reduction in analyst following is associated with increased agency costs.

However, despite the important role of financial analysts in the market, there is a wealth of evidence that their recommendations may not be based entirely on the information provided in corporate reports. De Bondt and Thaler (1990) explain that whilst financial analysts would be expected to be a source of rationality in the market, they too are subject to overreaction and can make irrational predictions. They are inefficient in the way in which they incorporate new information in their forecasts. Financial analysts may also be motivated to act in the interests of their careers. They may also use heuristics which lead to bias. Their cognitive limitations in processing large amounts of complex data may result in forecast errors.

According to existing research, analysts are more likely to be promoted if they issue “buy” recommendations of firms which have an existing relationship with their employers (Hong & Kubik, 2003). The incentive to further their careers links to herd behaviour. Analysts are likely to issuer fewer contrarian recommendations for fear of the reputational harm they may suffer if their predictions were incorrect. In these cases, it may be better to fail together than alone (Scharfstein & Stein, 1990).

Recent research on analysts introduces the concept of team dynamic amongst analysts who work together to issue recommendations (Gao & Rozenbaum, 2022). Analysts typically work in teams with a hierarchy based on the extent of experience. The lead analyst would delegate relatively simpler tasks to the junior analysts, based on the junior analysts’ competence. Tasks that are perceived to require more skill and experience, such as interactions with management of investee companies are usually undertaken by the lead analyst themselves. Although analyst reports typically only name the lead broker, the process of developing the recommendation requires a team effort. Gao and Rozenbaum (2022) used a regression model to determine how recommendations are affected by lead analysts compared to the effect of the more junior associate analysts. They found that the experience of the associate analysts explained more of the variation in forecast accuracy than lead analysts. However, the experience of the lead analysts explained more of the variation in forecast timeliness and the stock price reaction to reports. The authors inferred that the building of forecasts based on empirical models is likely delegated to associate analysts. However, the qualitative aspects of the report and access to management are tasks for which the lead analysts are responsible. It follows then that the effect of bias on recommendations may vary depending on the source of the bias within the team of analysts. In addition, the team dynamic may have the potential to mediate the effect of bias from individuals within the team. The study calls for further research into the effect of team dynamics amongst analysts. Specifically, research is required to answer whether analyst bias is mostly attributed to associate analysts.

Prior research also shows that the recommendations and information provided by analysts affect share price information. In evaluating confidence levels of financial analysts, Du and Budescu (2018) provide a possible explanation for low accuracy of share price predictions from analysts. They postulate that analysts trade accuracy for informativeness when making forecasts. This research supports the notion of analysts as key contributors to the flow of information in the market.

2.9.2. Analysts as purveyors of information

Analysts can be regarded as consumers of information since they use information in financial statements to develop their recommendations. Equally, they can be regarded as purveyors of information as they release recommendations to buy side analysts who make investments decisions on behalf of institutional investors. Besides the specific services to buy-side analysts, sell-side analysts appear to make a significant contribution to the information environment as a whole. For example, Mola, Rau and Khorana (2013) found that firms that lose all analyst coverage suffer a significant reduction in the trading volumes. The study also showed that firms that lost all analyst coverage were significantly more likely to delist than their peers.

International research on analysts has focused on the accuracy of their forecasts and determinants thereof. Research on the use of analyst reports provides insight into their effect on the capital markets and the mechanics of the investment decisions in the equity markets. Chaudhury, Sahoo and Dawar (2022) focused on the way in which sell-side research is used by buy-side analysts in the emerging market of India. The authors found that sell-side forecasts are used as a preliminary view before the institutional investor's team does their own checks. Evidently, the accuracy and reliability of the sell-side research is confirmed through this additional research. The benefit of sell-side research is that buy side analysts need not start their research from scratch, especially when there is a new company that is being analysed. The relationship between buy- and sell-side analysts appears interactive as the study's participants explained that calls or meetings with the sell-side analyst are sometimes required to understand and justify the reasoning for certain elements of the forecasts.

It is evident that there are similarities between sell-side analysts and preparers of financial statements – firstly, both parties provide information to the markets and secondly, the consumers of their information require some sort of assurance that the information is reliable.

2.9.3. Trends in the sell-side research industry

Analyst coverage has the potential to enhance the efficiency of capital markets by improving the information environment of firms. In turn, an improved information environment has a positive effect on the liquidity of firms that are covered by analysts (Brown *et al.*, 2015; Chen, Xie & Zhang, 2017). However, in the traditional sell-side research industry, analysts are not compelled to follow any specific firm. One of the factors that influences analysts choice of coverage is the level of disclosure from the firm (Healy & Palepu, 2001). Where firms provide useful voluntary disclosures, the cost of acquisition of information for analysts will be lower, making it easy to cover the firm. This availability of information has the potential to allow analysts to generate new information for potential investors, such as share price forecasts and recommendations. However, analysts may be unable to provide any informational advantage where a company provides high quality information (Mensah & Yang, 2008). As a result, there may be a reduction in demand for the information provided by the analyst (Healy & Palepu, 2001).

Hettler, Skomra and Frost (2023) offers possible reasons for declining sell-side analyst coverage. Firstly, there has been a global shift towards passive, index-tracking investments. This trend is also evident in the JSE (Peerbhai, 2022). As a result, budgets for sell-side research at global investment banks were halved between 2008 and 2017.

Another factor that has potentially contributed to a global reduction in demand for sell-side research is the EU's second Markets in Financial Instruments Directive (MiFD II). The directive requires financial institutions to separate the costs of execution and trading from analyst research. Despite the MiFD's extraterritorial applicability (-, 2023), impact assessments, such as those provided in PwC (2016) appear to be concentrated in EU markets. The impact on the JSE is likely to have been indirect, as global asset managers divert resources in response to the restrictions posed by MiFID II. Buy-side firms are required to, amongst others, make explicit payments for research and show that research contributes to improved investment decisions. Sell-side firms are required to identify services that could be categorised as research and therefore for which payment would be required. As a result, smaller research providers could struggle to charge buy-side firms for their research. Ultimately, decisions to continue to provide coverage on certain firms would require cost-benefit assessments.

Evidently, a key determinant of analyst coverage is the benefits associated with that coverage for the analysts. Sell-side analysts are more likely to follow large firms with high trading volume so that sufficient commissions can be generated (Hettler *et al*., 2023). As a result, smaller, thinly traded firms which stand to benefit the most from improved information environments are less likely to attract analyst coverage precisely because of their lack of visibility and poorer information environments. This concern is noted by Hettler *et al*. (2023) in the study titled "The great sell-side sell off". The author explains that whilst it makes economic sense to reduce or discontinue coverage of smaller firms due to lower demand for their research, it is these firms from which market participants can derive the most benefit from analysts coverage due to their weak information environments.

In response to the conundrum of poor analyst following and weak information environments, asset management firms offer corporate sponsored or commissioned research. This type of research is paid for (or commissioned or sponsored) by the firm being covered so as to achieve greater visibility amongst investors. It is clear that when research is paid for by the subject company, conflicts of interest will naturally arise. However, brokerage firms have tried to minimise this conflict by instituting policies that restrict the analyst or the firm itself from holding and trading client stock or even maintaining other business relationships with clients. Kirk (2011) found that sponsored research reports have information content for investors based on 2-day abnormal returns. Notably, these results were strongest for research from firms that had these conflict of interest policies in place.

However, related research, based on actual stock return and analyst data, offers evidence to the contrary. Billings, Buslepp and Huston (2014) compared subsequent stock returns of companies that had sponsored research to those of companies that were independently covered. The results showed no significant difference in the subsequent returns of both groups of companies. Similarly, no significant differences in forecast accuracy were found between the two groups of companies. These findings are supported in Campbell, DeAngelis and Moon (2019), which used data from the popular social media outlet, Seeking Alpha. The study included an analysis of the tone of the analysts' reports, the disclosed position of the analyst and subsequent returns of the shares. This type of analysis was superior to analysis in an experimental setting, which, as the authors argue, inherently removes the effects of the analysts' reputations. Findings revealed that where the tone of an analyst's published research is contrary to their own positions in the stock, responses by investors are magnified. This response suggests that investors view a position as an information signal in its own right. These findings support the assertion that since analysts have a vested interest in the shares that they cover, their analysis is likely to be more rigorous and timelier and may indeed, be a valid means of filling the void left by declining sell-side analyst coverage.

Research on the Singapore Stock Exchange proffers a potential solution to the issues of declining analyst coverage, whilst maintaining a level of independence of the analyst. Markov and Tan (2014) provide an evaluation of the intermediated model of research, pioneered by the Singapore Stock Exchange (SGX) and the Monetary Authority of Singapore. The scheme was launched in 2004 and has a strong participation rate amongst SGX-listed firms. The findings suggest that the intermediated model is a viable alternative to a traditional sell-side research model and the sponsored research model. This is because the scheme targets the firms that would not attract sell-side research in a traditional model due to their relatively smaller size. The analysis showed that the probability of coverage for the smallest firms increased from 6.83% to 16.61% under the intermediated model. The model also shows notably less optimism in intermediated research recommendations compared to sponsored research recommendations. The scheme reports were found to have noticeable information content, as evidenced by significant average abnormal event day returns. Collectively, these findings suggest that it is possible to have an information environment in which the informational benefits of analyst coverage are achieved without concerns about potential conflicts of interest.

In a South African context, academic research on commissioned research for JSE-listed firms is, to the researcher's knowledge, non-existent. Yet, commissioned analyst coverage is only *relatively* new. For example, Blue Gem Research is a company that offers only client sponsored research. According to a web page from as far back as a decade ago on the company website, Blue Gem Research was founded to address a "structural bottleneck in the South African equity market" (Blue Gem Research, 2023). The post further details the issue that analysts are incentivised to cover the most liquid shares in order to monetise their research. Furthermore, investors and the companies themselves can benefit from commissioned research. The web page is clear that the company produces "commissioned research" (in bold font on the web page).

The focus of the empirical work in this study is on independent sell-side analysts, although the effect of sponsored research is explored in relation to the findings of the interview process.

2.10. Complexities in the interpretation of financial statements

Notwithstanding the uncertainties precipitated by audit failures, the interpretation of financial statements requires expertise and judgement. In attempting to satisfy the information requirements of a variety of users with different levels of expertise and expectations, financial statements have become complicated (Pascual-Ezama *et al.*, 2018; Y. Zhang, De Zoysa, & Cortese, 2019). As a result, the users of these financial statements need to use a significant amount of cognitive processing and judgement (Joffe, 2020). This increased use of judgement is likely to involve heuristics and bias.

Kahneman and Tversky (1982) consider the influence of natural language in situations of uncertainty. The way information is communicated may lead, intentionally or unintentionally to incorrect notions being transferred from authors of information to users thereof. The literature on integrated reporting shows how information is selected to portray companies in a favourable manner. The interviewed institutional investors in Atkins and Maroun (2015, p.210) revealed perceptions of "harmless impression management" in integrated reports. They acknowledged that whilst the information in the reports is unlikely to be false, the reports have been "carefully and deliberately worded".

Van Nieuwerburgh and Veldkamp (2009) also consider the consumption of information. They contend that it is the ability of investors to absorb information that is limited and not the availability of information. In prior research, Kilka and Weber (2000) controlled for information asymmetries by providing investors with equal access to both local and foreign companies. The findings still showed that investors are more confident in their forecasts of domestic stock returns. The evidence from these studies suggests that the consumption of information may be subject to irrationalities which arise not exclusively because of asymmetric information.

2.11. Cognitive and emotional biases

Tversky and Kahneman (1974) in their seminal work, identified specific heuristics or mental shortcuts which are used by individuals to reduce cognitive load. These heuristics, the authors explained, lead to behavioural biases. Cognitive behavioural biases are the result of an inappropriate application of heuristics in the decision-making process. In research on the functioning of cognitive processing systems, Tversky (1974) acknowledges that whilst heuristics can sometimes lead to irrational bias, they are a thrifty yet effective way of making estimations for the purposes of decision-making. Behavioural biases may also arise from emotions, and these are classified as emotional biases. Here, individuals are able to apply reason to a situation or problem, but their eventual reactions are influenced by emotion-driven impulses (Elster, 1998).

In this study, both cognitive (heuristic-driven) and emotional biases are examined. However, the analysis is limited to biases from the seminal research on heuristics (Tversky, 1974; Tversky & Kahneman, 1974; Kahneman & Tversky, 1982; De Bondt & Thaler, 1985; Barberis & Thaler, 2003; Shiller, 2003;) as well as those that are commonly applied to trading behaviours (for example, Barber & Odean, 2001), based on a bibliometric analysis. The behavioural biases are discussed in the rest of this section.

2.11.1. Herd behaviour

The literature on herd behaviour in the context of analysts comprises firstly, studies which focus on the analysts herding around the forecasts of other analysts or general market sentiment and secondly, studies which focus on institutional investors herding in their reaction to analysts' recommendations. These research perspectives are evidence of the dual role of analysts in the information environment – they act as both users of information and producers of information. In fact, the use (or non-use) of information in situations of uncertainty is central to the definition of herding.

In his seminal work, Keynes (1937) explains the root of herding as doubting the accuracy of one's own judgement in the presence of uncertainty. As a result, individuals default to the crowd, which is viewed as better informed. Herding is therefore simply defined by Banerjee (1992, p.798) as "everyone doing what everyone else is doing, even when their private information suggests doing something quite different". In the context of analysts, Trueman (1994) conducted one of the first studies that challenged the assumption that analysts' recommendations reflect all their private information. They found that analysts tend to release forecasts that are similar to their own prior forecasts and the prevailing consensus.

Herd behaviour has been explained using Bayesian models. These models are predicated on the notion that the actions of others constitute information which influences the probability estimations of subsequent decision makers. In updating their own estimates, individuals use Bayes' rule and will revise their estimations using the information conveyed by previous decisions. In a Bayesian model, the underlying premise is that economic decisions are the result of mental processes involving an algorithmic incorporation of prior information. However, the outcome can be sub-optimal if individuals follow an incorrect track, based on previous incorrect decisions. In addition to the explanations of herding provided by economic models, studies from psychology and sociology consider the potential impacts of personality and social settings on herd behaviour. Cao, Hao and Yang (2023) considered the effect of an analyst's culture of origin on their propensity to herd. They found that analysts that came from cultures classified as collectivist displayed increased tendencies toward herding. Although the effect of culture is moderated by the analyst skill, it is exacerbated by task difficulty.

Herd behaviour is closely related to other biases. Anchoring (Tversky & Kahneman, 1974) refers to the tendency of individuals to make estimates based on an adjusted initial value. Cen, Hilary and Wei (2013) found that equity analysts tend to anchor their earnings forecasts on industry medians despite company fundamentals justifying a higher/ lower estimate. In this way, firms with higher growth prospects than their peers had lower forecasted earnings than their company fundamentals suggested. There is also a relationship between herding and overconfidence. When analysts deviate from the herd because of their prior accuracy (Clement & Tse, 2005), they may be displaying overconfidence (Hilary & Menzly, 2006). In addition, there is a further link between the optimism displayed towards a stock and the tendency to herd. Chiang and Lin (2019) explain that analysts may be reluctant to reveal a negative view of a stock and so will be less likely to be the first to issue downward recommendation revisions. This implies that analysts' proclivity for herding may be different for upward and downward revisions.

Herding has been classified as either intentional, when it is as a result of the three motivation categories from Keynes (1937) or spurious, when it arises from trading similarities based on the same informational and/ or regulatory motivations (Bikhchandani & Sharma, 2000). Institutions react to the same piece of information released by the company, and this results in trades in the same direction (Guo, Holmes & Altanlar, 2020). The distinction between intentional and spurious herding is important as spurious herding can be viewed as being rational. It is rational for investors to buy (sell) a stock for which positive (negative) information has been released. Amongst buy side analysts, Bennett, Sias and Starks (2003) contend that behaviour that is perceived as herding may simply be a result of correlated trades amongst institutions with the same investment philosophy. It may appear that institutional investors are herding in buying the same shares after an upward target price revision and when they sell the same shares after a downward target price revision.

Despite the difficulties involved in distinguishing between spurious and intentional herding empirically (Bikhchandani & Sharma, 2000), recent studies examine the robustness of their findings in relation to common information. For example, Lin (2018) reports that their results are robust with respect to common and earnings information. Differentiating spurious from intentional herding was the focus of Guo, Holmes and Altanlar (2020). To conduct their empirical analysis, they developed hypotheses based on a comparison of market signals and contrarian trades.

Several studies have found evidence of herding amongst analysts and institutional investors. However, there is some divergence on the influence of circumstances and the motivations for herd behaviour. For example, Brown, Wei and Wermers (2014) found a greater tendency to herd on negative stock information. The authors contend that this is because of the more severe reputational and litigation risk of holding poorly performing shares. However, Chiang and Lin (2019) assert that analysts are reluctant to reveal negative perceptions of a stock and therefore less likely to herd around downgrade recommendations. Similarly, Song, *et al.* (2009) find that where there is more uncertainty regarding a specific firm, there is greater incentive to provide new information to the market and therefore, less incentive to herd. In contrast, Tikoo and Wen (2022) infer from their findings that the uniqueness of corporate strategy is positively related to herding as analysts are more likely to herd where information asymmetry is greater.

Herding can lead to inefficiencies in the financial markets as individuals ignore their own choices and follow others even if they are not sure if the latter are making the right decisions. In such situations, an individual makes a decision based on the decision made by the individuals before them, but not the information on which the decisions were based. As a result, each decision maker can be either uniformed if they have no information of prior signals or informed, if they are aware of prior decisions. However, as noted by Banerjee (1992), this signal may be incorrect. Clement and Tse (2005) find that herding forecasts tend to be less accurate than bold forecasts. Such a reduction in informativeness can be so severe, contends Banerjee (1992), that society would be in better position if they compelled economic participants to use only their only information. Kim and Pantzalis (2003) provide empirical evidence of this inefficiency as they find that herding amongst analysts reduces the market value of the companies that they cover.

Scharfstein and Stein (1990) proffer herd behaviour as a partial explanation for excessive volatility in the capital market. Market participants will exacerbate exogenous price shocks if they follow the trading behaviour of others (e.g. buying when others are buying). Evidence to support this notion was provided recently by Gu, Guo and Zhang (2022) in a study which reflected the institutional investor tendency to overreact to analyst price revisions. This behaviour in turn exacerbates mispricing in the stock market. This trading behaviour is consistent with the notion of information cascades (Bikchandani & Sharma, 2000). An informational cascade occurs when it is optimal for an individual to follow the decisions of those ahead of them and ignore their own information. As this trend in decision making continues with each subsequent decision maker, eventually, a decision maker will ignore their private information entirely and use only the information gained from previous decisions. Once this point is reached, all subsequent decisions are uninformative to others.

Keynes (1937) provided three main motivators of herding behaviour – learning, reputation and/ or “beauty contests”. These motivations are specific to the analysts. Regarding analyst-specific attributes, herding has been associated with analyst experience (Hong & Kubic, 2003) and frequency of forecasting (Clement & Tse, 2005). In addition to analyst attributes, subsequent research has also identified firm-level and macro-economic contributors to herding. However, Banerjee (1992) also found other instances of herding, in which there are no principals or agents. In the context of analysts, Cao, Hao and Yang (2023) examined the influence on culture on proclivity to herd. Although the latter may be argued to be “analyst-specific”, it represents an extension to the specific motivators identified in Keynes 1937).

Consistent with the reputational motivations for herding, Scharfstein and Stein (1992) cite the principal-agent issue, where analysts can be regarded as the agents, having to convince the principals (their clients) of the accuracy of their recommendations. Keynes (1936), as cited in Scharfstein and Stein (1990, p. 465), suggests that investors and managers may have increased proclivity to herd behaviour if they are concerned about how others will assess their ability to make good judgements as “worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally". Trueman (1994) was one of the first to test the reputational motivation to financial analysts; if analysts do not follow their peers, they risk poor performance in relation to the consensus. On the other hand, if they cluster around the consensus, they may pursue artificially attractive opportunities. Herding is therefore linked to fear, greed or reputational concerns amongst analysts (Banerjee, 1992).

Proclivity for herding has also been shown to vary with the level of information available (Kim & Pantzalis, 2003). Information-related motives can be both firm-specific and analyst-specific. Kim and Pantzalis (2003) found that herding increases in relation to companies that are more diversified. Furthermore, analysts have been shown to deviate from the herd as their experience increases (Hong *et al.*, 2003; Clement & Tse, 2005). Similarly, Hirshleifer, Levi, Lourie and Teoh (2019) find evidence of fatigue and decreased accuracy when analysts issue several recommendations in a single day. Notably, the market acknowledges this phenomenon and discounts for analyst fatigue.

It is apparent that there have been divergent findings in the studies on herding. These are not entirely explained by the difference in time periods or market. A detailed review of the measurement approximations in the studies on herding revealed that the divergent findings do not appear to be driven by the measurement approximations used. For example, both Kim and Pantzalis (2003) and Song *et al.* (2009) use the clustering around the consensus as a measurement approximation for herding. Yet, the former find that herding is more pronounced when analysts cover more diversified companies and the latter find that there is less herding when earnings uncertainty is higher. It may not be possible to reconcile these findings when interpreting them from the perspective of earnings uncertainty. It becomes even more perplexing when one considers that the same measurement approximations were used. However, a deeper analysis reveals that Kim and Pantzalis (2003) focused on US-listed companies while Song *et al*. (2009) focused on the Korean market. These findings reveal the interconnectedness of the various factors that may influence herding and highlights the importance of considering them together.

However, a poor information environment appears to underpin several motivations for intentional herding in the literature on herding. In one of the first empirical studies on herding of analysts, Barron and Stuerke (1998) found that the dispersion in analysts' earnings forecasts can serve as an indicator of uncertainty about the firm's earnings. These results suggest a positive association between uncertainty and herding. Leece and White (2017) show that consumers of information (analysts) tend to exhibit a greater degree of herd behaviour in environments where the quality of information is lower. In these environments, the more capable analysts act first and the less capable analysts follow. Similarly, independent analysts were shown to herd with affiliated analysts because of the latter's superior access to information from management (Xue, 2017). A more recent study (Segara, Wu & Yao, 2023) considered the level of intangible assets reported on the balance sheet. Intangible assets are known to be relatively difficult to value than tangible assets in terms of the International Financial Reporting Standards. It was found that firms that reported greater levels of intangible assets were associated with greater levels of herd behaviour amongst analysts, indicative of the importance of the information environment.

For the purposes of this study, H2 and H3 are disaggregated into the following sub-hypotheses relating to herd behaviour:

H2.d. Poor quality integrated reports increase analysts' proclivity to herd behaviour.

H3.d. Herd behaviour has an effect on the quality of the forecasts of equity analysts.

2.11.2. Overconfidence

Overconfidence is one of the more widely researched biases, even in relation to the financial markets. The ubiquitous nature of the bias was emphasised by Daniel Kahneman who mentioned in a 2015 interview that the trait that he believes is most likely to lead to flawed judgements is overconfidence (Shariatmadari, 2015). The author of several seminal works on heuristics and biases, Kahneman, went on to say that if he had a magical wand, he would eliminate overconfidence. Similarly, DeBondt and Thaler (1995 p.402) suggest that the bias of overconfidence is possibly the "most robust finding in the psychology of judgement".

Moore and Schatz (2017) point out that studies on over-confidence have applied the term broadly. Studies on confidence and self-efficacy lack the comparison of belief to reality which is required for any assessment of *over*confidence (emphasis added). For an individual to be assessed as being overconfident, they must have higher levels of confidence than can be justified by reality. The authors further explain that research that compares belief with reality employs one of three measures: overplacement, overprecision or overestimation. Overplacement refers to an individual's unsubstantiated belief that they are better than others. Overestimation refers to an individual's belief that they are better than they actually are. When individuals display overprecision, they are too certain that they know the truth. As detailed in the following paragraphs, some of the seminal research on overconfidence in the context of financial markets has applied the measures of overplacement, overprecision and / or overestimation jointly to evaluate the potential effects of overconfidence on trading behaviour.

Kahneman refers to overconfidence as a type of overoptimism (Shariatmadari, 2015). This overoptimism permeates all three measures identified by Moore and Schatz (2017). For example, overestimation is essentially being overoptimistic about one's skills and abilities in relation to others. In his research on unrealistic optimism, Weinstein (1980) explained that feelings of unjustified invulnerability are not merely characteristics of an optimistic outlook on life but rather an error in judgement. Individuals tend to think that it is less likely for negative events to occur in their lives compared to positive events. This is because they focus on factors that positively influence their chances of good fortune, forgetting that others have the same factors in their favour. In the context of the three facets of overconfidence from Moore and Schatz (2017), this feeling of unjustified invulnerability is an example of overestimation and overplacement.

Another perspective on overconfidence is the overestimation of one's own role in prior positive outcomes. This phenomenon is known as "self-serving attribution" (Miller & Ross, 1975 p.213). Individuals tend to afford too much credit for their successes to themselves, whilst insufficiently considering the contribution of circumstances outside of their control. Conversely, this effort-result covariance is not cited under conditions of failure. This notion of self-serving attribution has been explored in notable seminal works, subsequent to Miller and Ross (1975). Heath and Tversky (1991) posited that individuals are more likely to bet in uncertain events in contexts where they consider themselves to be experts. Then, the individual will attribute an accurate estimation to their own knowledge, while failure will be attributed to chance. In this case, the self-serving attribution arises due to the individual's perceived expertise in the given context. In seminal work, Daniel, Hirshleifer and Subrahmanyam (1998) used the bias of self-serving attribution and the overweighting of private information to develop a model for under- and over-reactions on the stock market.

Weinsten's (1980) insights on unjustified invulnerability were applied to the financial markets by Hilary and Menzly (2006). Equity analysts were found to become more confident and more likely to deviate from the consensus (with an incorrect prediction) after a short streak of forecasts that were more accurate than the median. The focus of Hilary and Menzly's (2006) research was on short term dynamics instead of long-term trends. This self-attribution bias is so pervasive that it can result in individuals misrepresenting their prior predictions to match the knowledge that they gained in hindsight (Fischoff, 1982). Experimental research by Pikulina, Renneboog and Tobler (2017) supported these findings. Overconfident investors were found to over-invest. Notably, investment decisions were more closely associated with investors' perceptions of their financial knowledge (relative to peers) rather than investors' actual financial knowledge.

Barber and Odean (2001) and Odean (1998b) attribute high levels of trading on the equity markets to overconfidence. They explain that overconfident investors trade more frequently than the rest of the market (overplacement, as per Moore and Schatz, 2017) and because they are too certain of their own views of the future (overprecision, as per Moore and Schatz, 2017). They therefore frequently feel that they have identified arbitrage opportunities where other investors have not. This belief in their own abilities is not supported by the performance of their investments. To test their hypotheses, Barber and Odean (2001) compared the performance of shares that were purchased to shares that were sold. They found that the shares that the overconfident investors bought underperformed those that they sold.

Overconfidence has been shown to result in a greater propensity for risk taking (Moore & Schatz, 2017). Confidence is useful when it helps individuals overcome their natural inclination to avoid taking required risks in competitive settings Moore & Schatz, 2017). The market may be viewed as a setting in which some level of risk-taking is required by all participants. However, as Moore and Schatz (20017) caution, the trait of confidence is distinct from overconfidence in that the latter incorporates a false estimation of one's capabilities. We deduce that the key to distinguishing confidence from overconfidence, is the ability of the individual to accurately estimate their own capabilities (Moore & Schatz, 2017; Lundeberg, Fox & Punćcohaŕ, 1994). In the psychology research, calibration refers to the "degree of fit between a person's judgment of [their] performance and his or her actual performance" (Bol & Hacker, 2012 p.1). This definition is illustrated by Lundeberg *et al*. (1994) who found that individuals who displayed lower levels of overconfidence had more accurate perceptions of their abilities, especially when their responses were likely to be incorrect. Similarly, Du and Budenescu (2018) posit that a well-calibrated analyst is able to correctly assess the accuracy of their forecasts while overconfident analysts will overestimate their accuracy in forecasts.

Another result of overconfidence is the lack of preparation and practice (Stuart, Windschitl, Smith & Scherer, 2017). The level of preparation required by an individual for a task depends on their estimation of the likelihoods of possible outcomes. Since overconfidence is essentially a miscalibration of an individual's own capabilities, overconfident individuals will overestimate the likelihood of a positive outcome (also consistent with the overoptimism referred to by Kahneman (Shariatmadari, 2015) and therefore deem less preparation to be required. In addition to being underprepared, overconfident individuals may not devote sufficient cognitive resources to the processing of information. They may even subconsciously ignore information that contradicts their existing beliefs.

In addition to showing the effects of overconfidence, the research has also examined the potential causes of the bias or the contexts in which proclivity for the bias is likely to increase. These factors can be broadly classified as either contextual or biographical. Overconfidence has been attributed to biographical and contextual factors. The research on biographical features and overconfidence is vast and likely to continue to grow, given the individual differences in overestimation and overplacement (Moore & Schatz, 2017). Lundeberg *et al.* (1994) drew on the educational psychology research that found that female students tend to underestimate their abilities, i.e. they were underconfident. This "bias" persisted in females, even when they entered the workforce. So prevalent is this underconfidence amongst females, that it earned its own label – the "Imposter Phenomenon" (Clance & Imes, 1978), and continues to attract research attention (see for example, Rice *et al.*, 2023). Lundenberg *et al.* (1994) found that levels of overconfidence were highest in undergraduate males. In the context of trading behaviour, this gender-overconfidence link has been extensively explored since the seminal work of Barber and Odean (2001). The authors tested for differences in trading behaviour between men and women. Their findings, later supported by Pikulina *et al.* (2017), showed that men traded 45% more actively than women. This evidence further endorsed the relationship between frequent trading and overconfidence and entrenched the notion that men tend to display higher levels of overconfidence than women, even as investors.

From a personality perspective, overconfidence, particularly the facet of self-serving attribution has been linked to locus of control (Miller & Ross, 1975). Individuals with an internal locus of control are more likely to perceive outcomes to be as a result of their own actions whilst those with an external locus of control are more likely to perceive outcomes as a result of circumstances beyond their control.

Environmental and individual factors have also been shown to increase the proclivity for overconfidence. Friesen and Weller (2006) link overconfidence in analysts to cognitive dissonance amongst financial analysts. They postulate that if an analyst issues an optimistic earnings forecast based on their own, private information, they are likely to interpret subsequent information in such a way that confirms their initially held position. In other words, new information is not given its due importance in the analysts' forecast due to overconfidence in their own, privately held information. This finding is supported by evidence that overreaction is more likely to occur when information has not yet been made public compared to after it has been released to the public (Daniel, Hirshhleifer & Subramanyam, 1998; Bassiere & Elkemali, 2014). The research affirms the notion that uncertainty intensifies psychological bias.

Seminal experimental research provided the initial evidence that overconfidence increases when the task at hand is difficult (Kahneman & Tversky, 1979; Shefrin, 2008). Miller and Ross (1975) suggest that, in tasks that are skill-dependent, individuals who are achievement motivated may develop an external locus of control as a way of defending their self-esteem. Individuals seldom acknowledge the limitations of their own knowledge by tempering their confidence in their responses. The overestimation of individual ability was particularly noticeable in groups of participants who knew the least of the subject matter. Notably, it was found that with increasing knowledge comes decreasing overconfidence until individuals become very knowledgeable about a topic. At this stage, they become underconfident. The authors conclude that “those who know more do not generally know more about how much they know” (p.179). This conclusion may be extended to imply that those who know little do not generally know how little they know and is referred to as the Dunning-Kruger effect (Dunning, 2011). The Dunning Kruger effect is supported by Lundenberg *et al*. (1994) who found the highest levels of overconfidence in *undergraduate* men (emphasis added). Although both men and women were confident, it was the less experienced men who displayed overconfidence in relation to their performance on a test. Women displayed a better assessment of their own abilities while the men, particularly undergraduate men, were most overconfident of their answers to more challenging questions.

These findings were supported by Shefrin (2008) who also found that that people tend to exhibit overconfidence when dealing with issues that involve prediction and uncertainty. In doing so, they over-emphasise the information they have. This tendency is particularly relevant in highly uncertain environments. Further similar evidence was provided by Mokoaleli-Mokoteli *et al.* (2009) who showed that some of the sampled investment analysts believed that they had a superior understanding of the market despite their recommendations having realised limited actual investment value.

For the purposes of this study, H2 and H3 are disaggregated into the following sub-hypotheses relating to overconfidence:

H2.b. Poor quality integrated reports increase analysts’ proclivity to the overconfidence bias.

H3.b. The overconfidence bias has an effect on the quality of the forecasts of equity analysts.

2.11.3. Availability

The availability heuristic was initially identified in the seminal work of Tversky and Kahneman (1974). Extending this research on decision-making, Kahneman and Tversky (1979) developed Prospect Theory. They showed that individuals assess equal gains and losses in an inconsistent manner as they displayed a disproportionate aversion to losses. Their incorporation of probabilities into situations was inconsistent with Bayes’ Law and expected utility as they tend to overweight events with low probabilities. Prospect Theory has since been applied to the financial markets in widely cited studies. For example, Barber and Odean (2008) found that investors tend to invest in shares that have recently been covered in the media. However, availability is not as prominent as overconfidence and herding. Fieder (2004 p.2) notes that “investors who trade according to an availability heuristic are less conspicuous”.

Being one of the “seminal heuristics”, availability has been used to explain other aspects of irrationality, such as “local bias” (Bailey, Kumar & Ng, 2011), “familiarity bias” (Tversky & Kahneman, 1974) and “first impression bias” (Hirshleifer *et al.*, 2021). The bias is also discussed in various studies whose focus is not directly on availability. For example, Bonner, Hugon and Walther (2007) conducted a study on the effect of the recommendations of well-known or “celebrity” analysts. As they employed the approximations of the quantity of media coverage the analysts receive, they inherently incorporate the availability heuristic.

Availability is closely linked to anchoring (Tversky & Kahneman, 1974). Analysts may be reluctant to deviate too far from their initial recommendation, or they may make insufficient adjustments to their initial estimates, due to the anchoring effect. Arkes and Blumer (1985) discuss this phenomenon as the sunk cost effect – there is a greater tendency to continue with a course of action once an investment in money, effort or time is made. Analysts, however, also invest time and effort into researching a company and developing their recommendations. It is expected then that they would be reluctant to alter their initial recommendations. The rest of this section details each aspect of availability, it's relationship with other biases and its application to the financial markets and analysts, in particular.

In situations where individuals assess the likelihood of an event based on the ease with which similar, past events can be recalled, they exhibit the availability heuristic (Tversky & Kahneman, 1974). It is the availability heuristic (also known as recency bias (Lee *et al.*, 2007) that leads investors to overweight current information in their forecasts. For example, the current business cycle is overweighted in the investment decision, resulting in a decision that is consistent with the current state (Lee, O'Brien & Sivaramakrishnan, 2008). Similarly, a user of financial information may overestimate the likelihood that the process of external verification was flawed based on the ease with which similar failures are recalled.

There are several factors that impact the ease with which individuals recall information. In this regard, Schneier (2008) provides broad categories on the factors that influence recall. Individuals will easily recall risks that have high impact, particularly if people have been impacted, and if those risks are widely discussed. It is these factors, together with the recency of the information, that are the focus of research on investors and analysts.

The timing of the release of information is a common factor that influences its ease of recall. Lee *et al.* (2008) reasoned that the availability heuristic will lead analysts to overweight current company performance in their forecasts. They explain that when current company performance is strong (weak), analysts will overweight the likelihood of strong (weak) growth in the future. Measuring forecast error as the difference between actual growth and forecasted growth, if current company performance is favourable, then availability will lead to overoptimistic growth projections. Conversely, if current performance is weak, then availability will lead to overly pessimistic growth projections (Lee *et al.*, 2008). The authors therefore hypothesise that if availability has an influence on analysts' forecasts, then current company performance should have a negative relationship with forecast errors. This reasoning is extended to the hypothesised relationship on business cycles and management's forecasts regarding internal company performance.

Ease of recall is not only influenced by time. Nofsinger and Varma (2013) incorporated the concept of a style of learning where investors repeat actions that previously resulted in favourable outcomes whilst they avoid situations that previously resulted in unfavourable outcomes. They find that retail investors often repurchase shares that they had previously sold for a profit, and more importantly, those repurchase decisions are not optimal.

Another factor that influences ease of recall is the familiarity of the piece of information. For example, the ease of recollection may be influenced by the extent of media coverage due to the significant impact of similar instances (Crotty, 2020). In the context of "celebrity analysts", Bonner *et al.*, (2007) find that investors overreact to forecast revisions issued by analysts with high levels of media coverage. The concept of similarity is extended by Becker, Proksch and Ringle (2022) who find that analysts issue more favourable recommendations when a company's CEO has a similar personalities to their own. Another manifestation of familiarity is "local bias", being the preference for shares of companies that are located in close geographic proximity to the brokerage firm (Bailey *et al.*, 2011).

For the availability bias, as with the other biases, uncertainty is a pivotal notion. Ganzach (2000) specifically considers the judgement of risk and return with regards to financial assets. They assert that when assets are unfamiliar, investors will default to easily available information about global sentiment towards the asset. For the purposes of this study, H2 and H3 are disaggregated into the following sub-hypotheses relating to availability:

H2.a. Poor quality integrated reports increase analysts' proclivity to the availability bias.

H3.a. The availability bias has an effect on the quality of the forecasts of equity analysts.

2.11.4. Loss Aversion

Expected utility theory, had been the accepted model of economic choice for individuals' choices under uncertainty since it was presented by von Neumann-Morgenstern (1944). However, systematic violations of expected utility theory, where decisions were made under conditions of uncertainty, paved the way for an alternative model of evaluating decision-making of individuals. Kahneman and Tversky (1979) presented prospect theory as an alternative . According to prospect theory, individuals exhibit behaviour consistent with maximising an "S"-shaped value function. A pivotal aspect of this value function is the reference point against which gains and losses are assessed. Usually the status quo is taken as the reference point but there are situations in which gains and losses are coded relative to an expectation or aspiration level that differs from the status quo. According to Prospect Theory, losses and gains are defined in terms of changes from what individuals subjectively perceive as a starting point – gains and losses are evaluated relative to an individuals' expectation.

In their experimental research, Kahneman and Tversky (1979) asked participants to choose between options with varying expected outcomes in hypothetical scenarios. Several significant findings were recorded in the research. Individuals tended to overweight outcomes that are certain compared to those that are probable, a phenomenon termed, ""the certainty effect". The study also found that most individuals dislike symmetric bets, with this aversion increasing as the stakes increased. Specifically, they found that "losses loom larger than gains" (Kahneman & Tversky, 1979 p.279). In other words, individuals experienced the pain of losing money more intensely than the joy of gaining the same sum of money. In fact, Thaler (2000) asserts that losses hurt individuals about twice as much as gains make them feel good.

Another manifestation of prospect theory is the status-quo bias (Samuelson & Zeckhauser, 1988). Applying status-quo bias, Thaler and Benartzi (2004) found that if employees' savings rates were automatically increased as their salaries increased, they did not feel as though they were making sacrifices today for future savings. This is because their disposable incomes still increased, albeit by a reduced amount.

Prospect Theory has been cited as an explanation for several other behavioural tendencies. Shefrin and Statman (1985) extended prospect theory to the disposition effect - the phenomenon whereby individuals sell shares that have gained value too soon and hold on to shares that have lost value too long. This is because of the tendency to avoid regret. Due to their desire to avoid regret, investors will tend to hold their losing investments too long and sell their winners too soon; they labelled this tendency the “disposition effect” (Odean,1998a). A manifestation of loss aversion is therefore the tendency to sell winning shares too soon and hold losing shares too long. Similarly, Barber and Odean (2008) explain how the effects of the bias exacerbate the reluctance to sell underperforming shares. They explain that due to our psychological heritage, individuals are disposed to hold on to under-performing shares and to realise gains too soon by selling winners.

However, emerging evidence does not always support the tendency for losses to loom larger than gains. Harinck, Van Dijk, Van Beest and Mersmann (2007) found that gains loom larger than losses for small amounts of money. The authors suggest that this is because, in the context of financial losses, individuals are aware that minor incidents will have a smaller impact on their lives than major financial incidents. Individuals also have more exposure to small financial losses than large ones. As a result, they may overestimate the impact of large losses. Mukherjee, Sahay, Pammi and Srinivasen (2017) affirm the magnitude effect on loss aversion. Loss aversion was found to disappear for higher monetary values, if a relatively larger “gain” anchor is provided. Loss aversion has also been found to vary according to age, income, wealth and education (Gächter, Johnson & Herrmann, 2022). Collectively, these studies provide strong evidence for loss aversion being dependent on the type of decision and the contexts in which the decision is made.

As with the other biases discussed in this study, the research on loss aversion also highlights the impact of the information environment. Asquith *et al.* (2005) focused on the analysts' consumption of information. They found that the quantum of increase in the earnings of firms added to a strong buy list was less than the quantum of decrease of shares added to the strong sell list. This implies that the increase in stock price before it was recommended as a “buy” would be less than the decrease in stock price before a “sell” was recommended.

With regards to the analysts' role as a provider of information, loss aversion is often documented in relation to institutional investors' reactions to analyst recommendations. For example Barberis, Shleifer and Vishny (1998) find that institutional investors react more strongly to downgrades than to upgrades. This evidence is consistent with the prospect theory hypothesis that individuals tend to feel the pain from losses more than the pleasure from gains. Investors have been found to hold losing shares too long and sell winning shares too soon (Odean, 1998a; Krishnan & Booker, 2002; Balkanska, 2018). These results were robust to considerations of portfolio balancing and taxation-induced sales. Krishnan and Booker (2002) found that the information provided in analysts' reports can reduce disposition effect-induced errors. In an experiment, the authors compared the likelihood to sell shares to the likelihood to buy shares, where analyst reports of varying degrees of detail were provided. It was found that a summarised report reduced the disposition effect for gains only. However, when the level of detail in the report increased, the disposition effect was reduced for both gains and losses. Balkanska (2018) also viewed the analyst as a provider of information. They found that the disposition effect is exacerbated for shares with higher forecast dispersion (and therefore higher uncertainty). This finding, consistent with that of Krishnan and Booker (2002), evidences the higher propensity of investors to realise gains when facing information uncertainty.

For the purposes of this study, H2 and H3 are disaggregated into the following sub-hypotheses relating to loss aversion:

H2.c. Poor quality integrated reports increase analysts' proclivity to loss aversion.

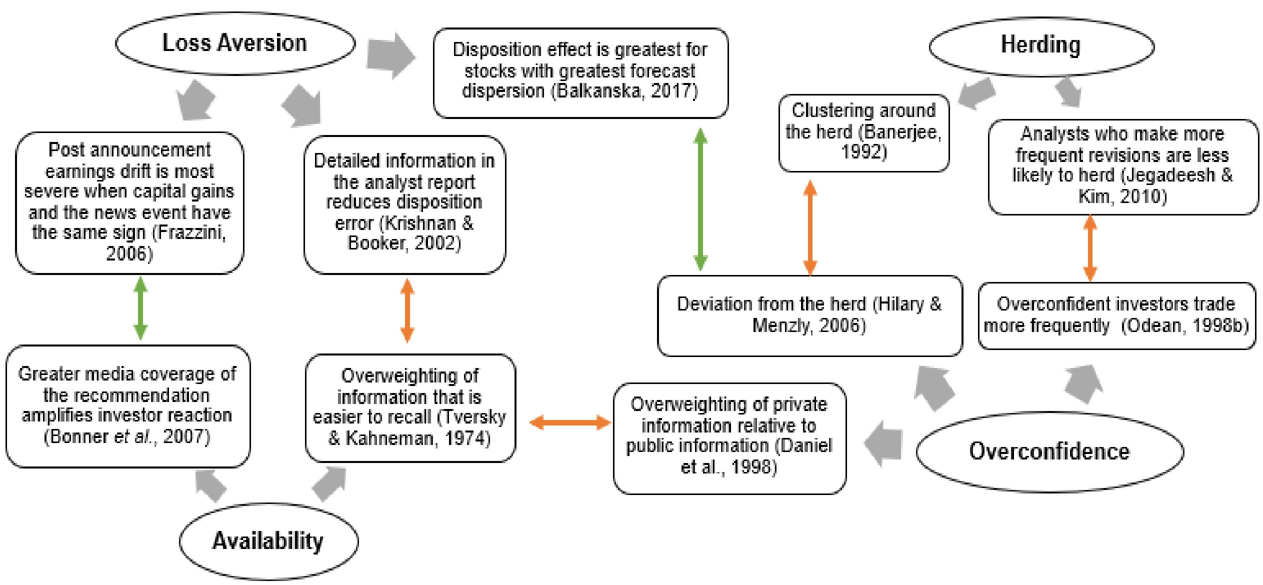
H3.c. Loss aversion has an effect on the quality of the forecasts of equity analysts.

2.11.5. Relationships between the biases

Having explored the various attributes of the biases in the prior sections, this section details the relationship between the biases. All cognitive processes are inter-connected, by virtue of the very nature of the human mind (Bruckmaier, Krauss, Binder, Hilbert & Brunner, 2021). Yet, these connections may pose challenges in the research. For empirical studies, measurement approximations are usually formulated with reference to specific attributes of the bias (further detailed in Section 2.14.2. on Approaches to the quantification of bias). If these attributes are correlated in some way, then this may pose challenges with regard to the robustness of the analysis. Furthermore, inferences drawn from the results would need to incorporate the possible contemporaneous effects of the other biases. Liu, Peng, Xiong and Xiong (2022 p.716) refer to the "bias zoo" which has resulted from the plethora of behavioural finance research over the recent decades. They explain that several biases can offer similar explanations for any single type of trading behaviour. Challenges arise in determining the relative importance of the biases and in determining whether an apparent "bias" is a result of other non-behavioural factors.

The relationships between the biases covered in this study are depicted in Figure 6: Relationships between the biases, with confirmatory associations shown with green arrows and apparently contradictory associations shown with orange arrows. The relationships are synthesised in the rest of this section.

Figure 6: Relationships between the biases



Source: Author's own

According to Hilary and Menzly (2006), overconfident analysts are more likely to deviate from the consensus. However, clustering around a piece of existing information (e.g. consensus), whilst ignoring private information is considered herding (Banerjee, 1992). This negative association between herding and overconfidence is further evidenced by the findings of Odean (1998b) and Jegadeesh and Kim (2010). The former study found that overconfident investors trade more frequently while the latter study found that analysts who make more frequent revisions are less likely to herd.

A positive association between the disposition effect and overconfidence may be inferred from the findings of Balkanska (2018), that the disposition effect is greatest for shares with the highest forecast dispersion, and Hilary and Menzly (2006), that overconfident analysts are more likely to deviate from the herd. Yet, the focus of the study from Balkanska (2018) provides a finer perspective – their focus was on the uncertainty associated with the shares, for which forecast dispersion was used as a proxy. Comparing these studies highlights the importance of an understanding of the full context and objectives of the studies on biases in the markets.

The availability bias leads to the overweighting of information that is easier to recall. Factors that can affect recall are the recency of the information, with the latest information being overweighted in the decision. The disposition effect leads investors to sell winning shares too soon and hold on to losing shares for too long, ignoring available information that may advise otherwise. Yet, according to the findings of Krishnan and Booker (2002), investors who have an existing position and plan of action in relation to a stock, will be influenced by subsequently presented analyst reports. In fact, depending on the level of detail in the report, so pronounced was the emphasis on the report, that it influenced their trading behaviour. Perhaps these results combine to show that the recency of the information (availability) had a greater influence over the proclivity to sell winners and keep losers at incorrect times (disposition effect).

On overconfidence, Daniel *et al.* (1998) assert that the overweighting of private relative to public information is a manifestation of overconfidence, yet seminal research on availability (Tversky & Kahneman, 1974) explains availability bias as the overweighting of information that is easier to recall. This comparison indicates that a study involving private information (overweighted due to overconfidence) that is not easy to recall (underweighted due to availability bias), would need to take careful consideration of the context and any contemporaneous factors that could influence the inferences.

2.12. Other factors that influence analyst recommendations

Thus far, the literature review has centred on cognitive biases of analysts, in line with the research questions and hypotheses. However, any study that seeks to evaluate analyst forecast accuracy and/ or divergence in their recommendations, would be incomplete if it did not include factors relating to analysts' incentives and analysts' experience. These factors have been prominent in prior research relating to analysts. The rest of this section therefore includes a discussion on these factors.

2.12.1. Analysts' incentives

Besides their role in the dissemination of information in the capital markets, sell-side research generates trading commissions and investment banking business for their brokerage houses. Although incentive conflicts are not biases or heuristics, it is possible that they lead to optimism in analysts' forecasts.

Prior to 2003, the research on analysts had a strong focus on the incentive conflicts that arose from structural issues. For example, Hutton and Sloan (2000) investigated whether analysts affiliated with brokerage firms were more likely to issue more optimistic growth forecasts in order to attract and retain underwriting business. Hong and Kubik (2003) related career progression to optimism of analysts' forecasts. They cite the anecdotal evidence of Merril Lynch appointing a relatively inexperienced analyst to the coveted Microsoft account because he followed management's optimistic projections. This appointment was intriguing because another Merril Lynch analyst who used technical valuation models was not aligned to management's forecasts. Hong and Kubik (2003) found that analyst accuracy remains a key determinant in the career progression of analysts. However, when controlling for accuracy, they found that analysts who issue proportionately more optimistic forecasts are more likely to move up the brokerage hierarchy. Furthermore, analysts were found to be judged less on accuracy when it came to coverage of shares that had a relationship with their brokerage houses.

Hong and Kubik (2003) found that accuracy was less important than optimism during the stock market boom in the 1990's. Analysts were rewarded more for their optimism than forecast accuracy by their brokerage houses. They also linked analysts optimism with analyst experience, with younger analysts seemingly more optimistic than their older peers. The authors postulate that this may be a result of younger analysts who want to build a reputation in their brokerage houses and then potentially "cash out" as they become older (Hong & Kubik, 2003 p. 346). Interestingly, Hong and Kubik (2003) found that younger analysts tended to be less bold than their older counterparts. The authors suggest that this may be a manifestation of younger analysts needing to build a favourable reputation with their brokerage firms.

These types of incentive conflicts led to the Global Analyst Research Settlement in 2003 in the United States of America. The agreement was reached after investigations into potential conflicts of interest faced by sell-side equity analysts in the United States of America (Barber, Lehavy & Trueman, 2007). The analysts were accused of compromising the integrity of their research in order to generate business for the investment banking divisions of their employers. According to the agreement, the ten global investment banks were required to separate their investment banking and research businesses (Barber *et al.*, 2007).

The GRAS was applicable to the US-operations of 10 global banks. These banks are listed in Appendix L. One of these firms is Morgan Stanley & Co. Incorporated (Morgan Stanley). Morgan Stanley's policy regarding conflicts of interest for research analysts is published on their website (Morgan Stanley, 2019). It relates to research analysts who publish equity, fixed income and derivative research reports. The policy stipulates that "research analysts are not directly supervised by personnel from other areas of the firm (in particular investment banking or sales and trading personnel)". The policy further requires that analysts' compensation is not directly linked to specific transactions, particularly in the investment banking business.

South African banks have their own internal policies on managing the incentive conflicts that arise between the research and investment banking businesses. For example, the Standard Bank Group has a published policy for managing conflicts of interest relating to investment research (Standard Bank Group, 2024). As with Morgan Stanley's policy, the policy of Standard Bank Group stipulates that "No part of the analyst's remuneration was, is or will be directly or indirectly related to the specific recommendations or views expressed in the report". Furthermore, the policy states that no members of the research department (analysts) are supervised by employees in Investment Banking. The policy stipulates the determinants of analysts' remuneration. They are:

- The Analyst's individual performance and productivity;

- The overall quality and accuracy of the Analyst's research;
- Evaluations by investor clients and employees in other parts of SBG with whom the Analyst interacts,
- The size and trading value of, the profitability of, and the potential interest of, SBG's investor clients in Research with respect to the asset class covered by the Analyst; and
- SBG's overall performance.

Notably, quality and accuracy of research are key criteria upon which analysts' performance are evaluated.

Following the Global Research Analyst Settlement (GRAS) Agreement in 2003, there are still several studies on incentive conflicts, although with a focus on the effectiveness of the terms of the agreement. When comparing the recommendations of investment banks to those of independent research firms, Barber, Lehavy and Truman (2007) found that banks were reluctant to downgrade shares whose prospects dimmed during the bear market in the early 2000's. Brown et al. (2015) provided further evidence that supported the persistent influence of conflicts of interest. Their evidence was obtained from direct interaction with analysts via survey and interviews. 44% of analysts surveyed cited the importance of generating underwriting business or trading commission to their compensation. However, the findings from Wu, Wilson and Wu (2017) suggests that the terms of the GRAS agreement were effective in tempering unsupported optimism amongst analysts. The study assessed the efficacy of the GRAS in mitigating the observed optimism in recommendations provided by analysts affiliated with merger and acquisition advisory firms for the covered company. The levels of optimism in forecasts from affiliated analysts was compared to the levels of optimism in forecasts from unaffiliated analysts prior to and following the GRAS. The finding of a reduction in optimism levels of affiliated analysts lead the authors to infer that the GRAS was effective. In doing so, they also affirmed prior findings that the excessive optimism of affiliated analysts before the GRAS was due to conflicts of interests.

Besides the conflicts covered by the Global Analyst Research Settlement, prior research shows other incentives for analysts to issue optimistic recommendations. Subsequent to the research by Hong and Kubic (2003) and the Global Analyst Research Settlement, other studies have focussed on other motivations for optimistic forecasts. For example, a study of German fund managers found that younger fund managers were found to rely more on conversations with management than their older counterparts (Drachter, Kempf & Wagner, 2007). Whilst the study focused on fund managers instead of sell-side analysts, the idea of younger investment professionals issuing more optimistic forecasts (Hong & Kubic, 2003) is consistent with the need to build a reputation early on in their careers (Drachter *et al.*, 2007).

2.12.2. Analysts' experience

Several studies support the notion of an improvement in analyst forecast accuracy as experience increases. Using a sample of forecasts from 236 analysts over the period 1980 to 1995, Mikhail, Walther and Willis (1997) examined the impact of analyst experience on the accuracy of their forecasts, as well as the market's response to these forecasts. They found that analyst forecast accuracy improves the longer the analyst follows the company. In addition, the market tends to afford more weight to forecasts from more experienced analysts. Clement (1999) used a larger sample size (6468 analysts) and a broader set of variables (including portfolio complexity) than Mikhail *et al.* (1997). The later study affirmed the existing findings of the positive association between forecast accuracy and experience. More recently, Bradley, Gokkaya and Liu (2017) examined the effect of the type of professional experience that analysts acquired prior to becoming an analyst. They found that prior experience in the industry of the firms that the analyst covers, is positively associated with forecast accuracy. Furthermore, when these industry-experienced analysts cease coverage of firms (for exogenous reasons), the firms experience significantly larger increases in information asymmetry, than when other analysts cease coverage.

Mikhail *et al*. (1997) highlighted an important perspective of analyst experience in their acknowledgement of their study's limitation. They recognise that their findings do not explain exactly *why* the forecasts of more experienced analysts are accurate. There are of course, the potential effects of a learning curve that accompany increased experience, but increased experience is potentially equally concomitant with improved social and professional networks in the industry. Despite the extent of related research on analyst experience, this distinction made in a widely cited, seminal paper, remains relatively unexplored. The link between analyst experience and access to management is intriguing, given the importance of direct contact with management as a source of information for analysts' forecasts. For example, over half of the analysts interviewed by Brown, Call, Clement and Sharp (2014) reported that they had direct contact with company management (CEO or CFO) typically four or five times a year. The study concluded that private communication with management plays a greater role in shaping forecasts than the analysts' own evaluation of the company's financial performance. The prior research therefore shows that analyst experience is an important determinant of the accuracy of recommendations, although the exact reasons for this phenomenon warrant further exploration.

2.13. Knowledge gap

The research on analyst bias focuses on determining firstly, *whether ("if")* analysts are prone to specific biases (for example, Bernhardt *et al.*, 2006; Song *et al.*, 2009), secondly, the *contexts ("when")* in which each bias is likely to affect their forecasts (for example, Hilary and Menzly, 2006; Lee *et al.*, 2008) and thirdly, the possible reasons ("why") for these biases (for example, Zhang, 2006; Bessiere & Elkemali, 2014). There appears to be a gap in the academic research that offers specific debiasing strategies that could be of practical relevance (in other words, the "what next?").

Research on bias, even beyond the contexts of analysts, tends to focus on a single bias at a time. Whilst this type of research has the advantage of excluding the relationships between biases (see Section 2.11.5: Relationships between the biases), it avoids a detailed interrogation of the choice of measurement approximations and the contextual implications of the principles used to derive them. These studies also have limited generalisability as they do not mimic the real context of analysts as individuals, prone to several biases simultaneously.

The existing research on integrated reporting, on analysts' forecasts and on the behaviour of the capital market as a whole, appear to have been done in isolation. The integrated reporting research has focused on the usefulness of integrated reports to investors (Atkins & Maroun, 2015; Pistoni *et al.*, 2018) and has even proffered integrated reporting as a means to evaluate the quality of decision-making functions within the organisation (Ecim & Maroun, 2023). Analysts have been researched as consumers of information in corporate reports. Their biases have attracted significant research attention, as have the effects of their recommendations on the market. The cognitive psychology research focuses on the decision-making process amidst uncertainty (Kahneman & Tversky, 1982; Tversky & Kahneman, 1974) and effects thereof on the functions of equity markets. Yet, each respective research area does not follow the flow of information from its preparation to its consumption by the entire capital market. The combination of these somewhat isolated strands of research, in the context of information preparation and consumption presents a largely unexplored avenue for research. This research aims to fill the apparent gap by exploring the potential influence of integrated report quality on the analysts' forecasts. It combines aspects from the decision-making process of analysts with the quality of integrated reports, a revolution in corporate reporting and governance (Eccles *et al.*, 2019), and a window to the firm's inner workings (Dimes & de Villiers, 2023).

2.14. Methodologies in the Corporate Reporting and Finance Literature

2.14.1. Qualitative Analysis

The literature on information quality in the financial market predominantly employs quantitative methods. Brown and Hillegeist (2007) analysed the relationship between disclosure quality and information asymmetry. As a proxy for disclosure quality, the authors used analysts' evaluations of firms' disclosure activities from the Association for Investment Management and Research (now known as the CFA Institute). They acknowledge the limitations of these and other empirical proxies of disclosure quality.

Hopwood (2007) bemoans the fact that accounting research has become disconnected from the practice of the craft. There are few field studies that have focused on the contexts in which accounting information is used. Qualitative interviews may address this lacuna in the research. In order to avoid the reductionist potential of empirical proxies and to capture the nuances in users' thought processes, prior studies in corporate reporting and on financial analysts have employed quantitative and qualitative methods respectively in their evaluation of biases.

Whilst quantitative methods are predominant in finance research, Dewasiri *et al.* (2018) argue that the use of proxy variables alone may not be sufficient in explaining financial behaviours and decisions. The gap between real behaviours and proxy explanations may be narrowed by using supplementary approaches. Many decades ago, the seminal work of Lintner (1956) was one of very few qualitative finance research papers. Now, there appears to be a growing strand of finance research that uses qualitative data to understand investor sentiment and behavioural finance patterns. Kearney and Liu (2014) review the methodologies in sentiment and behavioural finance. The authors describe key sources of qualitative information that have been used by finance researchers to study investor decisions. These sources include media articles, internet messages and analyst reports.

The qualitative finance research appears to be dominated by the grounded theory paradigm. In a grounded theory study, the researcher aims to provide an explanation or an understanding of a process (Creswell & Poth, 2016). The present study focuses on the process of analysts' decision-making involved in developing share price forecasts. It is in line with similar studies on analysts and investment decision-making, which also employ grounded theory approaches. For example, Holland (2006) employed a grounded theory approach to determine the main sources of uncertainty for fund managers when making asset allocation decisions. Coleman (2014) explored the reasons for the impracticality of application of neoclassical investment theory in the real world. Imam and Spence (2016) sought to explain the work that financial analysts do by undertaking a field study. More recently, Chaudhury *et al.* (2022) use a grounded theory approach to explore the interaction between sell-side and buy-side analysts. These studies are all exploratory in nature and deal with phenomena that are not readily quantifiable using measurement approximations.

2.14.2. Quantitative Analysis

The methodologies in existing empirical research on the quality of integrated reports is dominated by regression analyses (for example, Barth *et al.*, 2017). This research uses structural equation modelling (SEM). The SEM approach can be described as a combination of related statistical techniques. A structural relation refers to the connections between latent variables (or unobserved variables) that are estimated through multiple observed variables. SEM therefore consists of a group of quantitative data analysis techniques (path analysis and confirmatory factor analysis) to test whether relationships between observed variables are as per the developed hypotheses (Schumacker & Lomax, 2004).

Whilst SEMs may be regarded as regression equations that model relationships between observed and latent variables (Kline, 2015), the methodology is superior to regressions which do not account for random measurement error and relationships between independent or exogenous variables. SEM allows for the statistical evaluation of pre-established theoretical and measurement hypotheses using real-world data. Particularly relevant for this research is the ability of SEM to model numerous dependent variables, whether latent or observed, within a single model. As a result of this capability, SEM can be considered a second-generation multivariate technique.

SEM is particularly useful in analysing complex, context-dependent phenomena (Bollen & Noble, 2011) as it accommodates latent constructs or variables that cannot be directly observed. SEM has been widely used when quantifying behaviour (Bollen & Noble, 2011) as latent constructs can be created from measurement indicators. Furthermore, using SEM, the researcher can determine the degree of measurement error in each indicator and whether all of the indicators behave as hypothesised, in relation to the underlying latent variable. The issue of measurement error is particularly relevant to the variable that represents integrated report quality. The present study treats the variable as a latent construct with various measurement indicators.

2.14.2.1. Structural Equation Modelling in Accounting and Finance Literature

In recent decades, there has been an increase in the use of Structural Equation Modelling (SEM) as a method of data analysis in accounting research. One of the first accounting studies to use latent variables in a regression (Ittner, Larcker & Rajan, 1997) examined the factors influencing the combination of financial and non-financial measures in executive's performance contracts. The study involved the quantification of theoretical constructs such as strategy, regulatory environment and CEO influence, by using indicators and latent variables. Shields and Shields (1998) realised the potential of SEM as a method of analysis in practitioner-focused accounting research. Subsequently, Smith and Langfield-Smith (2004) identified twenty articles which used SEM across six leading accounting journals for the 21-year period to 2001. The number of articles increased to 37 in the 11-year period 2000 to 2011, across eight leading journals (Herda, 2013).

Typically, SEM is used in the accounting research to test relationships between and causal effects of the behaviours of managers and accountants in practice. This nomological approach is illustrated in Shields and Shields (1998), where the authors investigated the reasons for management participation in the setting of budgets. In their review of the empirical literature, the authors found that participative budgeting (independent variable) influenced behaviours and motivation of managers (dependent variables). Similarly, Viator (2001) studied the association between accounting mentorship, job performance and stress. More recently, Phan, Mascitelli, and Barut (2017) used a structural equation model to determine the factors which influenced adoption of International Financial Reporting Standards by practitioners in Vietnam.

It is in the analysis of unobserved/ latent variables (such as motivation and willingness to change) that SEM is superior to regressions (Shields & Shields, 1998; Smith & Langfield-Smith, 2004). These variables, unlike financial data, are not directly measurable and typically composed of a series of individual items or indicators. Another key benefit of the SEM approach is that multiple measurement approximations (or indicator variables) can be used to measure a latent construct (Kline, 2015). This approach is superior to the more commonly used regression models which accommodate one measurement proxy per variable at a time. For example, Lee (2023) used the deviation of target prices from benchmarks in their regression model to the effect of overconfidence in analyst recommendations. However, Moore and Schatz (2017) propose that overconfidence is not a "single unitary construct" (p. 8) and they suggest three forms of overconfidence (discussed in detail in Section 2.11.2. of this study). They call on researchers to employ, clear, robust measures to identify the presence of overconfidence. This reasoning may be applied as a motivation for the use of latent variables to model any behavioural bias.

Research that uses the SEM analysis typically employs survey questionnaires to gather data. This is consistent with the behavioural accounting research. Viator (2001) and Phan *et al.* (2017) both used survey responses from accounting professionals. Schmidt, Riley and Church (2020) considered the factors that contributed to accountants' reluctance to adopt data analytics technology. Their questionnaire comprised several scales from prior research. For example, the construct of "perceived value" was adapted from a prior study on consumer trust and the construct of "switching benefits" was adapted from another prior study on perceptions of adopting technological innovations. However, Hoffmann and Fieseler (2012) developed their own questions for each variable (and therefore, for each latent construct) in their research. Exploratory factor analysis was used to evaluate the effect of non-financial factors on companies' valuation. Similarly, Newman, Gamble, Chin and Murray (2013) developed their own questions based on the findings of prior literature. As is typical of research designs involving SEM, the surveys comprised several Likert-scale questions. The questions were formulated to measure constructs (or unobserved variables) from the prior social science and behavioural research.

SEM approaches can also incorporate financial data as indicator variables (for example, see Titman and Wessels, 1988). Although "largely neglected" (Baranoff, Papadopoulous & Sagar, 2007 p.654) and less popular than survey-based SEM data, financial data has been used in seminal and more recent works on capital structure. Capital structure researchers frequently acknowledge that the results of their studies are likely to vary depending on the measurement of leverage that is used. To overcome the measurement issues that arise when using proxy variables, Titman and Wessels (1988) used the factor-analytic technique of linear structural modelling. For their measurement model, accounting data was used as indicators for unobservable, firm-specific attributes. They explain that while firm-specific antecedents of capital structure cannot be observed, other observable variables (indicators) can be expressed as a linear function of the unobservable attributes. In their structural model, the relationship between debt ratios and the attributes defined in the measurement model was analysed. A similar approach was used by Ittner *et al.* (1997). They used accounting data and information from remuneration policies to derive measurement indicators for latent variables depicting factors that could influence the combination of financial and non-financial performance measures. For example, the latent variable of "strategy" comprised four indicators, derived from reported financial data. The four indictors were the ratio of research and development to sales, market to book ratio, ratio of employees to sales and the number of new product introductions. Each indicator had relevant theoretical substantiation. For example, the ratio of research and development to sales was chosen as an indicator variable for strategy because it provided a measure of the firm's propensity to search for new products. To substantiate this, the researchers cite Hambrick (1983) – prospector firms invest more heavily in research and development than defender firms because they engage in more innovation to identify new products or markets. Financial data were also used to derive indicators by Baranoff *et al.* (2007) in a study on risk and capital structure in the life insurance industry. In the measurement model, two indicators were used for asset risk and two indicators were used for product risk. The inputs for calculation of these indicators were market and accounting data.

Despite the benefits of using SEM, it remains under-utilised in accounting research relative to other disciplines such as management, marketing and information systems (Phan, Joshi & Mascitelli, 2018). Hampton (2015) suggests various reasons for this under-utilisation. SEM has not been widely incorporated into accountancy curricula and therefore remains a complex statistical technique to several accounting researchers. Furthermore, SEM is a continuously evolving technique, so researchers need to constantly consult with diverse types of material to keep abreast of latest developments. In addition, behavioural accounting data is likely to violate one or more of the SEM assumptions.

Although there are widespread calls for the utilization of SEM in various disciplinary contexts, research specialists also offer cautious perspectives on its application. Pearl and Mackenzie (2019) bemoan the betrayal of the theoretical underpinnings of path analysis by certain applications thereof. The authors assert that with the availability of computer packages to calculate path coefficients, path analysis became a "rote method" (Pearl & Mackenzie, 2019 p.86) as researchers did not need to have an understanding of the method before they applied it to their data. The authors cite a limitation of path analysis being that it assumes that the relationships between variables in the path diagram are linear. However, Kline (2015) asserts that curvilinear and interactive effects can be analysed in SEM. They also explain that SEM models assume probabilistic causality and not deterministic causality. While deterministic causality implies that a modification in a causal variable will consistently yield the same consequence across all instances of the outcome variable, probabilistic causality permits the occurrence of probable outcomes (Kline, 2015).

2.14.2.2. Quality as a latent construct

A key feature of the analysis in this study is the treatment of the quality of integrated reports as a latent construct. "Quality" is an inherently subjective and context-specific construct. As discussed in earlier sections, latent variables are not directly measurable and analysis thereof should incorporate measurement error. Borsboom, Mellenbergh and van Heerden (2003) contend that the difference between latent and observed variables is epistemological. In addition to the commonly used criteria of observed variables having no measurement error (Kline, 2015), Borsboom *et al.* (2003) sets out the additional criteria that observed variables must be deterministic, causally isolated and of equivalent cardinality. Further, the author posits that a variable may be latent for one researcher and observed for another. The example of gender is given – a researcher may treat gender as a latent variable because "the inferences from the data structure to the variable structure are epistemically certain" (Borsboom *et al.*, 2003 p.31). The author goes on to explain that variables in which a practitioner is used as a measurement instrument can be considered latent. Similarly, using the example of anxiety, Piasta (2010) explains that any single, observable measure of anxiety is unlikely to provide a reliable measure of the construct. In addition, scores to measure anxiety may not be the same if it is given at different times or if equivalent forms of the measure are given at the same time.

For the purposes of this study, the quality of integrated reports is represented by the average of the detailed scores of the adjudicators in the EY Integrated Reporting awards. These scores were awarded according to the categories as set out in the Integrated Reporting Framework. For example, each adjudicator would have rated each integrated report based on the adherence to the Guiding Principles in the Integrated Reporting Framework. A similar process would have been followed for the Content Elements and Fundamental Concepts indicators. The scores used in this research were therefore subject to the judgement of experts and are therefore inherently susceptible to measurement error. This is supported in Barth *et al.* (2017), where it was deemed necessary to measure inter-rater reliability amongst the experts. Integrated Report Quality (IRQ) is comprised of the "aspects" of "Fundamental Concepts", Content Elements" and "Guiding Principles". These aspects of quality are the observed, indicator variables that comprise the measurement model in the SEM analysis of this research. The report quality scores were assigned per report, per aspect of quality, by experts. This is not dissimilar to the gathering of data using a survey questionnaire, with each question being an indicator. In this research our "instrument" was the scoring sheet for each company-year that was used by the experts to evaluate the quality of reports.

In structural equation modelling (SEM), serial correlation among measurement indicators (in this case, the scores by each expert adjudicator) is not considered a significant problem due to how SEM treats relationships between latent variables and their measurement indicators. In fact, correlated errors between indicators reflects that these indicators are capturing related aspects of a latent variable. This prevents serial correlation from posing significant problems.

2.14.2.3. Approaches to the quantification of biases

Biases are difficult to quantify. Lee and Lee (2015) explain that biased behaviours cannot be practically observed, which limits the ability of researchers to detect such behaviour. Although the authors mention this in the context of herding behaviour, it is equally applicable to all the biases included in the present study. In fact, Frieder (2004 p.5) chose specific biases to include in their study based on "their ability to accommodate empirical testing". Evidently, the research on bias in the context of trading behaviours appears to be dominated by studies which take a positivist approach by determining a measurement approximation for the bias/es. Durand, Newby, Tant and Trepongkaruna (2013 p.104) also observe that the “caricature of the ‘typical’ behavioural finance research paper” is to infer underlying psychology motivating the behaviour of investors from empirical analysis of price data. This observation is based on the plethora of research that uses stock prices as the primary input in the measurement approximations for bias. These studies are not limited to selected biases, contexts, time periods or findings. A trend is observed where the seminal studies which define the bias and show its effects on decision making are usually experimental in nature. Subsequently, context-specific research on the bias, specifically with regards to the financial markets, usually employs stock return and forecast data in a model that is based on the principles established in the seminal work.

The rest of this section includes a detailed discussion of the approaches taken to derive a value for biases. These approaches are classified according to the categories of Measurement Approximations and Experimental Research. The section draws on the seminal behavioural studies (which have extensive inter-disciplinary applications) and then narrows focus on research in the context of the financial markets. To this end, the researcher undertook a bibliometric analysis by searching for articles that dealt with bias in the context of equity analysts. The studies yielded from the bibliometric analysis are synthesised to provide various insights regarding the quantification of bias, as in Tables 1 and 2.

2.14.3. Measurement Approximations

The practice of deriving or using a previously derived numerical value that represents a bias is ubiquitous. Measurement approximations are derived from ex-post trading data and analysts’ prior forecasts (for example, Clement and Tse, 2005; Barber and Odean, 2001). These approximations are then used in a form of quantitative analysis, most commonly a regression model. There is an emerging strand of research which uses survey data (typically Likert scale) in models in which biases are represented as latent constructs (see Section 2.14.2. on Structural Equation Modelling in Accounting and Finance Research.

2.14.3.1. Herding

As discussed in the literature review, there is a vast body of research on herding. In fact, our bibliometric analysts revealed that herding attracted the greatest amount of research attention from all the biases in the present study. A bibliometric analysis was conducted based on the Web of Science database. Search terms of “analyst”, “herding” and “herd behaviour” were used. A period filter from 1992 (the date of Banerjee’s seminal work on herding in the financial market) to 2023 was applied. A total of 164 records were returned, of which 20 were excluded from the analysis, because they were from unrelated disciplines. After filtering the results for studies from irrelevant disciplines and studies that did not contain measurement approximations, 46 studies remained. These studies were analysed in detail to determine the measurement approximations used, the context and findings. The results of this analysis are presented in Table 1: Measurement Approximations: Herding and discussed in the rest of this section.

The studies focus on testing whether herding exists and the situations in which analysts are likely to herd. The vast majority of studies use measurement approximations based on analysts’ forecasts, although the limitations of empirical analyses of the bias have also been acknowledged in seminal works. For example, Scharfstein and Stein (1990) explain that they can merely observe mutual funds trading together – they cannot directly observe that the fund managers are copying each other's trades. This limitation may partially explain the reason for the divergent findings on whether herding exists in certain situations or amongst specific groups of market participants.

A challenge faced by researchers who study herd behaviour is the differentiation of spurious and intentional herding. As discussed in the literature review, investors may be perceived to be herding (intentional herding) when they are merely reacting in a rational way to the same piece of information released by the company (Guo, Holmes & Altanlar, 2020). This distinction is difficult to make when dealing with historic data on analyst forecasts.

Although the literature on analyst herding is vast, the choice of measurement approximations appears to be clustered around a few seminal studies. This distribution is illustrated in Table 1, by means of the number of studies in the top left-hand corner of the cells containing each measurement approximation. From a chronological viewpoint, it appears that new approximations do not "replace" older ones. For example, one of the first measures of herding, developed by Lakonishok, Shleifer and Vishny (1992) has been used in studies as recent as Zhao, Xiang and Cai (2021), despite the development of other approximations in the interim. A similar inference can be made from the use of cross-sectional standard deviation (Christie and Huang, 1995) in Aharon (2021). A possible explanation for this "herding" around measurement approximations is that many approximations are derived from the same principle – analysts herd if they cluster around their prior forecasts and/ or the consensus forecast (Trueman, 1994). Barron and Stuerke (1998) incorporate this principle as they use the standard deviation of analysts' quarterly forecasts for the firm, divided by the average quarterly estimates for the same firm. Similarly, Christie and Huang (1995) use the cross-sectional standard deviations of returns.

One of the most ubiquitous measurement approximations was developed by Clement and Tse (2005). They focused on forecast revisions because they convey the analyst's information to the investors and usually elicit stronger reactions from investors. The study used the principle that analysts revise their forecasts to a lesser extent than is warranted by their private information (Trueman, 1994). As a result, there is a positive association between the revision and the forecast error. The authors also included a further prediction from Truman (1994) that small forecast revisions are more likely to be incomplete than extreme forecasts. Following these principles, a bold forecast will be one that is different from the analyst's prior forecast and the prevailing consensus. Forecasts that are between the analyst's prior forecast and the consensus forecast were classified as herding forecasts. The model therefore incorporated an indicator variable which took the value of 1 if the forecast was different from both the prior forecast and the consensus forecast, otherwise it took the value of 0. The popularity of this approximation persists, in studies as recent as Cheong and Lee (2023), where it was found that bold forecast for firms with low analyst coverage were the most profitable and Cao, Hao and Yang (2023) which found culture to have an effect on propensity to herd.

The majority of studies which use measurement approximations apply them in different contextual settings. These contexts relate to the analyst-specific, firm-specific or macro-economic circumstances. Studies usually focus on only one of these settings at a time and tend to use one measurement approximation for herding. The findings are largely similar in that they all find some evidence of herding. Contrarian views[5] were supplied by Barnhardt, Campello and Kutsoati (2006) and Mensah and Yang (2008). The former found that analysts do not herd as they systematically issue biased contrarian forecasts that differ from the consensus forecast in a direction consistent with their private information. Both studies argue that analysts have an incentive to differentiate themselves by providing forecasts that are significantly different from other forecasts based on commonly available information. Barnhardt *et al.* (2006) also included a detailed interrogation of popular measurement approximations. Notably, they assert that clustered forecasts do not necessarily imply herd behaviour. This is because earlier forecasts may contain information that subsequent analysts rationally incorporate into their forecasts (spurious herding, as discussed in Section 2.11.1. on Herding). The use of common information sources is also likely to result in clustering around the consensus. In their study, Barnhardt *et al.* (2006) used estimations of conditional probabilities which included the analysts' forecasts, consensus forecasts and conditioning events. This incorporation of conditioning events is different from other measurement approximations and captures confounding factors such as common information.

[5] Relevant studies are marked with an asterisk in Table 1.

Table 1: Measurement Approximations: Herding

Precedent	**Study**	**Context**
14 Clement and Tse (2005)	Hong, Kubik & Solomon (2000)	Analyst-specific
	Jegadeesh & Kim (2010)	Analyst-specific
	Salamouris & Muradoglu (2010)	Analyst-specific
	Clement, Hales & Xue (2011)	Analyst-specific
	Mira & Taylor (2011)	Analyst-specific
	Lee & Lee (2015)	Analyst-specific
	Hirshleifer, Levi, Lourie & Teo (2019)	Analyst-specific
	Choi, Mira & Taylor (2022)	Analyst-specific
	Limkriangkrai, Durand & Fung (2022)	Analyst-specific
	Cao, Hao & Yang (2023)	Analyst-specific
	Cheong & Lee (2023)	Analyst-specific
	Pisciotta (2023)	Firm-specific
	Segara, Wu & Yao (2023)	Firm-specific
	Kim, Kim & Shim (2023)	Analyst-specific
6 Lakonishok *et al.* (1992)	Mensah & Yang (2008)*	Regulatory environment
	Brown, Wei & Wermers (2014)	Analyst-specific
	Xu, Jiang, Chan & Wu (2017)	Analyst specific
	Lien, Hung & Chen (2020)	Analyst specific
	Zhao, Xiang & Cai (2021)	Regulatory environment
	Wen & Tikoo (2022)	Firm-specific
6 Christie and Huang (1995)	Barron & Stuerke (1998)	Analyst-specific
	Chang, Cheng & Khorana (2000)	Economic environment
	Gleason & Lee (2003)	Analyst-specific
	Palmon, Sarath & Xin (2020)	Analyst-specific
	Aharon (2021)	Analyst-specific
4 Jegadeesh and Kim (2010)	Frijns & Huynh (2018)	Firm-specific
	Lin (2018)	Firm-specific
	Chiang & Lin (2019)	Firm-specific
	Guo, Holmes & Altanlar (2020)	Analyst-specific
2 Chang *et al.* (2000)	Cakan & Balagyozyan (2014)	Economic environment
	Chong, Liu & Zhu (2017)	Analyst-specific
2 Gleason and Lee (2003)	Kim & Pantzalis (2003)	Firm-specific
	Song, Kim & Won (2009)	Firm-specific
2 Bernhardt, Campello and Kutsoati (2006)	Blasco, Corredor & Ferrer (2016)	Firm-specific
	Blasco, Corredor & Ferrer (2018)	Firm-specific
Banerjee (1992)	Xue (2017)	Analyst-specific

Precedent	Study	Context
Trueman (1994)	Clement &Tse (2005)	Analyst-specific
Chen and Jiang (2006)	Wang, Sun & Wei (2020)	Firm-specific
Barro and Stuerke (1998)	Garcia (2021)	Economic environment
Use of transition probability matrix in which the time series variability of the consensus compared to the analyst's forecast revision is used to define herding.	Welch (2000)	Economic environment
A comparison of whether an institution is a net buyer (seller) of a stock with the market-wide intensity for buying (selling) that same stock.	Gu, Guo & Zhang (2022)	Economic environment
Probability model	Frey, Herbst & Walter (2014)	Economic environment
Cross sectional standard deviation of returns	Christie & Huang (1995)	Analyst specific
Estimation of an objective function for the analyst where herding propensity is the cost of deviating from the consensus.	Huang, Krishnan, Shon & Zhou (2017)	Economic environment
Estimation of conditional probabilities including the analyst's forecast, consensus forecast and conditioning events.	Trueman (1994)	Analyst specific
Estimation of conditional probabilities including the analyst's forecast, consensus forecast and conditioning events.	Bernhardt, Campello & Kutsoati (2006)*	Analyst specific

** Indicates studies with contrarian findings*

Source: Author's compilation

2.14.3.2. Overconfidence

Seminal research on overconfidence from the cognitive psychology literature is dominated by experimental studies. Heath and Tversky (1991) conducted several experiments to explore self-serving attribution bias in situations of uncertainty, where betting was involved. The results showed that individuals prefer to bet on their own expertise over an equally likely chance event, but only in contexts where they considered themselves knowledgeable. To examine the effect of gender in overconfidence, Lundeberg, Fox and Punćcohaŕ (1994) asked three groups of psychology students to indicate their level of confidence in each of their answers to the questions in their examinations. This allowed the authors to examine the contextual determinants of overconfidence levels in males and females. Their findings, that overconfidence levels were highest in males who were less experienced, have found numerous applications in the literature on trading behaviour. Most notable amongst these studies is one by Barber and Odean (2001), which found that males displayed higher levels of overconfidence in their trading behaviours. The latter study used account data for households from a large brokerage, allowing for the analysis of the trading patterns of men and women over a six-year period. Similarly, the notion of the negative relationship between experience and overconfidence was applied to analyst forecasts by Dong *et al*. (2022). The study found that less experienced analysts are more likely to incorrectly overestimate the accuracy of their models and provide precise forecasts (i.e. with several decimal points) directly from those models.

As detailed in the literature review in Section 2.11.2. on overconfidence, three facets of the bias have been developed and applied theoretically – overprecision, overestimation and overplacement. To estimate the levels of these three facets, and consistent with the psychological term of "calibration", there should be a comparison between an individual's judgement of their performance and their actual performance. This comparison has found numerous applications in the research that seeks to evaluate the effects of overconfidence on trading behaviour. For example, Dong *et al.* (2022) did not only use the number of decimals in the evaluation of analysts' overconfidence. The study compared these overly precise forecasts with the actual stock performance to determine the analysts' calibration.

A bibliometric analysis was conducted based on the Web of Science database. Search terms of "analyst" and "overconfidence" were used, with a period filter from 1998 (the date Odean's seminal study on overconfidence in trading behaviour) to 2023. A total of 107 records were returned, of which 20 were excluded from the analysis, because they were from unrelated disciplines. Then, a further 65 studies were excluded because they did not contain measurement approximations for overconfidence. For example, Hegde and Zhou (2019) refer to trading volumes from the study of Barber and Odean (2001) but create measurement approximations for optimism because the latter is the focus of the study. A synthesis of the remaining 22 studies is contained in Table 2.

Studies presented in the synthesis include those that evaluate the overconfidence of analysts. Also included are studies that evaluate the moderating effect of analyst coverage on management overconfidence as well as analysts' response to management overconfidence in the companies that they cover. The latter studies are dominated by an approximation developed by Malmendier and Tate (2005), predicated on the notion that overconfidence may lead CEO's to overestimate the returns of their projects. They therefore believe that the stock price will increase in the future and prefer to exercise their stock options as late as possible. Therefore, the timing of the exercise of stock options is presented as the measurement approximation.

In the seminal work of Daniel *et al.* (1998), the authors developed a model that incorporated the principle of overplacement. As a result of overplacement, overconfident individuals tend to overreact to private information. The model has found subsequent application in several studies on the financial markets. In the context of analyst behaviour, this type of overplacement has also been applied relatively frequently, even in recent studies (for example Kim, Ryu & Yu

(2021)) and studies that do not rely on share price data. Machado and Lima (2021) for example, conducted a textual analysis of the tone of reports.

Self-serving attribution bias (also often cited with the Dunning-Kruger effect) is a facet of overconfidence that is widely understood and cited in the overconfidence research, yet difficult to measure as it requires an estimation of the analysts' own assessment of their efforts. For example, Dong *et al.* (2022) used a large number of decimals in an analyst's forecast to indicate that the forecast was derived directly from their model. In turn, this implies that the analyst is confident in their model and has not moderated the forecast estimate based on other potential influences.

The synthesis shows that empirical research tends to focus on one facet of overconfidence at a time. This is likely due to the use of models which incorporate a single measurement approximation for the bias. In addition, the majority of the studies evaluate the effect of overconfidence or proffer it as an explanation in studies which deal with related topics. There are very few studies which focus on determining whether overconfidence exists. This may be due to the difficulty in differentiating confidence from overconfidence and the focus of each study on a single aspect of overconfidence. The inferences that can be made from the studies' results are also bound by the measurement approximations chosen.

Table 2: Derivation of measurement proxies

Facet of overconfidence used to develop proxy	**Proxy**	**Study**
8 Overoptimism/ overestimation of future performance	Timing of exercise of stock options	Lin, Ho & Chih (2019)
	Timing of exercise of stock options	Wong, Lee & Chang (2017)
	Timing of exercise of stock options	Hsu, Novoselov & Wang (2017)
	Trading data	Hsieh, Bedard & Johnstone (2014)
	Timing of exercise of stock options	Lai, Li & Chan (2021)
	Remuneration of top three managers versus the industry	Zhang & Wang (2023)
	Self-serving attributional phrases inferred from archived public statements	Libby & Rennekamp (2012)
5 Overreaction to private information (overplacement)	Overreaction preceding a public announcement followed by an underreaction after the announcement	Bessière & Elkemali (2014)
	Underreaction following revisions that are contrary to their own beliefs	Kim, Ryu & Yu (2021)
	Overreaction preceding a public announcement followed by an underreaction after the	Friesen & Weller (2006)

Facet of overconfidence used to develop proxy	Proxy	Study
	announcement	
	Optimistic tone used in the analyst's report and the use of words that express exaggeration.	Machado & Lima (2021)
	Model development	Daniel, Hirshleifer & Subrahmanyam (1998)
4 Self-serving attribution bias 2	Precision of forecasts according to the number of decimal places, compared to actual stock performance	Dong, Liu, Lobo & Ni (2022)
	Forecast versus actual share price performance	Hilary & Hsu (2011)
	Number of superior predictions in the preceding four quarters.	Hilary & Menzly (2006)
	Number of first-person personal pronouns minus the number of third person personal pronouns	Czaja & Röder (2020)
2 Overconfident analysts are likely to trade more frequently than their peers (overplacement)	Frequency of forecasts issued.	Durand, Limkriangkrai & Fung (2019)
	Frequency of forecasts issued.	Limkriangkrai, Durand & Fung (2022)
2 Gender differences in overconfidence	Gender	Bosquet, de Goeij & Smedts (2011)
	Gender	Bosquet, de Goeij & Smedts (2015)
1 Overconfident analysts are likely to deviate from the herd (overplacement)	Deviation of target prices from benchmarks	Cheong & Lee (2023)

Source: Authors' own

2.14.3.3. Availability

The introductory paragraphs in this section dealt with the difficulties inherent in the quantification of biases. The availability bias is especially challenging to capture, so much so that Massa and Simonov (2006) propose that familiarity proxies be used to indicate available information. As explained in the literature review section 2.11.3. on the Availability bias, availability is defined with reference to the existing knowledge of the individual and the relative weighting they place on the various pieces of information that they have. In a financial market setting, this thinking process is captured by observing ex-post associations between a piece of recent information and subsequent forecast errors (Lee *et al.*, 2008).

As is apparent from the literature review section 2.11.3. on Availability, the application of the bias to investors, in general, appears to outweigh its application to analysts. A bibliometric analysis on the Web of Science database using the terms “analyst”, “availability” and “bias” yielded 249 results, many of which were irrelevant to the current study. After a comprehensive filtering of the results, only 15 studies on the availability bias in analysts remained. Of these, eight studies did not contain a measurement approximation for availability.

A relatively common[6] measurement approximation for availability involves a comparison between forecast errors and lagged earnings. This is predicated on the notion that if investors exhibit the availability heuristic, there will be an association between the availability stimulus and subsequent errors of forecasted growth. Specifically, the approximation for outcome availability includes daily market returns and contemporaneous stock returns to observe how investors perceive firm-specific events. The hypothesis is that, when there is a favourable market index return, investors may respond more strongly to contemporaneous upgrades, because of the availability of similar information.

The measurement approximations for availability appear very specific to the type of information that is considered easy to recall or overweighted in the individual’s decision. For example, Nofsinger and Varma (2013) examined whether retail investors would be more likely to repurchase a stock if they had previously sold it for a profit. Their measurement approximation was “repurchasing intensity”, measured as the number of repurchases scaled by the total number of purchases. A different approximation was used by Bonner *et al*. (2007) in their study on well-regarded analysts’ forecast revisions. The authors used the quantity of media coverage for the analysts’ recommendations as a proxy for availability. Another context-driven approximation was used by Frieder (2004). With regards to earnings announcements, where individuals overweight information they can easily recall, the author posited that there would be a disproportionate amount of buying (selling) activity after a notable positive (negative) earnings surprise. Specifically, the easily recalled information was measured as a once-off, abnormally large earnings surprise. The authors refer to this type of measurement approximation as “order imbalance data”.

However, Fieder (2004) also discusses the limitation of their measurement approximation – investors may be uninformed prior to the “stimulus event” (earnings surprise in the study) and the investors rationally use earnings surprises as a trigger for their trading activities. This observation reiterates the challenge of having to estimate market participants’ knowledge prior to the stimulus event when measuring availability.

2.14.3.4. Loss aversion

As explained in the Literature review section 2.11.4. of this study, loss aversion has been viewed as a manifestation of the disposition effect. Our bibliometric analysis therefore included the terms of “analyst”, “loss aversion” OR “disposition effect”. It was apparent from the results (27 articles, of which only three used measurement approximations) that the bias has not been extensively explored in relation to analysts.

[6] Used by Lee *et al.* (2008) and Klinger and Kudryavtsev (2010)

In relation to investors' trading data (Odean, 1998a; Balkanska, 2018), loss aversion is measured as the difference between the proportion of realised gains and the proportion of realised losses. The proportion of realised gains (losses) is calculated as realised gains (losses) scaled by realised gains (losses) plus paper gains (losses). The notion of "paper" gains or losses refers to a stock that remains unsold in the portfolio. The gains or losses are determined by comparing the opening and closing prices.

2.14.4. Experimental research

The limitations of the use of ex-post trading and forecast data to quantify bias in trading behaviours has been acknowledged by researchers. For example, Bernhardt *et al.* (2021) contends that the clustering of forecasts, widely used as an approximation for herding following Clement and Tse (2005) does not necessarily imply that intentional herding has taken place. There is always the possibility that analysts use common information sources – a feature that is not easily observable from ex-post trading data. Analysts work in a complex, "multi-task environment" (Francis & Philbrick, 1993 p.216). Their decisions are a function of various sources of information, sometimes available contemporaneously. The interaction of their technical expertise with career concerns and biases makes it difficult to isolate and capture the impact of a single factor from real-world data.

Experimental settings afford the researcher the benefit of control over certain factors that may influence the research. In their study on the disposition effect, Krishnan and Booker (2002) motivate their choice of experimental design. They explain that experimental designs enable better manipulation of the variables of interest. In their research, the authors were able to modify the contents of analysts' reports to show varying levels of detail, which was hypothesised to influence disposition error. In the experimental setting, the authors were able to control for tax considerations. This is not always possible with trading data, as applicability of tax provisions vary according to individual tax positions (not available from archival data) and types of trades initiated. It is also challenging to distinguish trades motivated by stock performance from tax-incentivised trades.

Certain salient features of decision-making cannot always be reliably inferred from trading data. Research on the disposition effect is equally interested in the likelihood of the individual to sell or buy, as it is in the actual sale or purchase transaction. In an experimental design, these nuances can be reliably captured by requesting participants to indicate their intentions in response to Likert-scale questions (Krishnan & Booker, 2002). Similarly, experimental studies allow researchers insight into the perceptions of investors. In their experimental design, Kadous, Mercer and Thayer (2009) were able to determine that investors are more likely to attribute an inaccurate, bold forecast to poor ability, whilst an inaccurate, herding forecast was attributed to factors outside of the analysts' control.

Despite these advantages of experimental research, the use of measurement approximations appears to be the most commonly used approach to quantifying bias. We suggest that this is likely because of the ease of access to ex post trading data and historic analyst forecasts. In addition to the ease of access, this data is available for large volumes of trades, across several analysts and in various markets, providing a sufficiently representative sample for use in various forms of econometric analyses.

Experimental research is also not without its limitations. Although some studies involve investors or professional analysts as participants (Krishnan & Booker, 2002; Kim & Shim, 2023), the majority appear to use surrogates for market participants. These surrogates are usually MBA or economics students (for example, Kadous *et al.*, 2009), who are likely to have some level of knowledge about the capital markets. There is an argument to be made that studies of bias relate to microeconomic behaviour and can contribute to the development of economic models (Kahneman & Smith, 2002). Certainly, seminal research including experiments (Tversky & Kahneman, 1974) has been applied to settings extending from financial markets (Lee *et al.*, 2008) to consumer choices (Thaler, 1980). However, arguments against non-natural experimental research are predicated on the notion experiments are by their nature, conducted in an artificial setting (Creswell & Creswell, 2017). For example, a decision to sell a winning stock sooner rather than later could be more tempting in a real-life scenario, where financial gains will be genuine.

2.15. Knowledge gap

Research on analyst bias is vast and incorporates various methods of analysis. Predominantly, these methodologies appear to be grounded in the positivist paradigm, with measurement approximations or survey results used as data for empirical analyses. There appears to be a gap in the literature which uses qualitative data to explore bias in the context of analysts. Recently, more studies have emerged which use qualitative data, even from interviews with analysts. Abhayawansa *et al.* (2019) interviewed analysts and produced a detailed description of their practices when assessing a firm and the information that they used. Chaudhury *et al.* (2022) use a grounded theory approach to explore the interaction between sell-side and buy-side analysts. These studies are all exploratory in nature and deal with phenomena that are not readily quantifiable using measurement approximations. There appears to be a paucity of research that provides insights that are obtained from direct interaction with analysts. Even fewer are the studies which employ a mixed methods design to explore bias amongst analysts.

2.16. Chapter conclusion

The key question is one of dynamics: how the economy adapts to new information, creates new knowledge, and how that knowledge is disseminated, absorbed, and used throughout the economy.

Stiglitz (2000, p. 1469)

This chapter detailed the “dynamics” of the information environment and used relevant theories and prior literature to develop a set of hypotheses. The creation of “new knowledge” was the focus of the literature on integrated reporting which is particularly relevant for the first research question and related hypotheses. The absorption and use of information was considered from the perspective of the literature on analysts and behavioural bias. These strands of literature are relevant for the second and third research questions. The chapter provides a review of various strands of literature and shows the common thread amongst them – the information environment.

Chapter 3: Methodology

3.1. Introduction

This chapter details the approach and procedures employed to address the research questions posed in this study. It begins with an orientation of the chosen methodology, being mixed methods. In Section 3.2, attention shifts to the ontological and epistemological foundations upon which this study is built with reference to a recapitulation of the study's purpose and related research questions. Being a mixed methods study, it was necessary to choose an appropriate mixed methods design. Section 3.3. therefore provides a detailed description of the research design and its appropriateness. Data considerations for the quantitative and qualitative analyses in this mixed methods design are discussed in section 3.4. For the quantitative analysis, this chapter also includes a discussion about the research instrument. Finally, considerations around validity and reliability of the method are discussed. According to the approach suggested in prior literature (Ihantola & Kihn, 2011; Creswell & Plano-Clark, 2018), validity and reliability considerations are presented separately for the quantitative and qualitative analysis sections and then specifically for the convergence of the quantitative and qualitative analysis.

The overall aim of this study is to evaluate the effect of corporate report quality and behavioural bias on the share price forecasts of sell-side equity analysts. A mixed methods design was chosen to improve the reliability of the findings by comparing the quantitative and qualitative results (Creswell & Plano-Clark, 2018). In doing so, this study provides insights that reflect the realities of practice (Coleman, 2014). Johnson and Onwuegbuzie (2004) explain that mixed methods can be particularly useful as the strengths of one method compensate for the weaknesses of the other method. In a study that involves behavioural bias which is challenging to quantify, but can also vary in different contexts, the juxtaposition of quantitative and qualitative analyses was particularly useful. Further detail on the mixed methods approach is provided in subsequent sections of this chapter.

3.2. Paradigm

This research was conducted within the pragmatic paradigm or system of philosophy. The researcher took the pluralistic view that quantitative and qualitative research are both useful and complementary (Johnson & Onwuegbuzie, 2004). Brierley (2017) promotes methodological pluralism as enabling researchers to be flexible in their choice of methods to address the objectives of each part of this study. In other words, researchers are not bound by specific ontological and epistemological issues and focus on employing methods most suitable for the answering of the research question. Similarly, Creswell and Plano-Clark (2018) suggest that instead of forcing a mixture of different paradigms, mixed methods studies, specifically those that employ a convergent design, should work from the more inclusive pragmatism paradigm. This suggestion builds on the work from Tashakkori and Teddlie (2003), who argued that the "forced-choice dichotomy" between the different worldviews should be abandoned. Instead, the focus of the study should be on answering the research question/s.

The mixed method in this study is therefore most appropriate under the pragmatic approach. This flexibility does not imply that there will be convenient methodology selection bias (Collins, Johnson & Onwuegbuzie, 2004). The rationale for the choice of methodology is explained in the rest of this section.

The positivist worldview is most common in finance research, which trends to be empirical. The development and testing of hypotheses arise from a positivist worldview in which researchers test an a priori theory. In the research on equity analysts, a positivist worldview appears to be the dominant worldview. One of the seminal works on sell-side analysts, Asquith *et al.* (2005) used a regression model to analyse empirical data extracted from a content analysis of analyst reports. Similarly, Ahmed and Flint (2020) employed various regression models to evaluate point and directional accuracy of analysts' forecasts. The models included variables of forecast and actual share price, similar to the quantitative analysis in the current research. A positivist worldview was also adopted by Harris and Wang (2019) as they compared the accuracy of analysts' earnings forecasts to forecasts obtained from other theoretical forecast models.

The limitations of quantitative research have a significant effect on the behavioural accounting research (Brierley, 2017). The use of measurement approximations for complex, real-life phenomena, such as heuristics and biases can be overly reductionist. In addition, quantitative methods can yield results that lack the context of practice or field research. As a result, they are too generalised to be applied usefully to individual subjects (Brierley, 2017).

Although not as common as positivism, constructivism is the dominant worldview in qualitative research in finance. Under this worldview, the existence of multiple realities is embraced, and participants' views are interpreted to build patterns and theories. Recently, there has been an increase in studies which adopt this worldview and employ grounded theory approaches in their research on equity analysts or fund managers (Holland, 2006; Coleman, 2014; Imam & Spence, 2016; Chaudhury *et al.*, 2022). These studies all seek to understand some aspect of application of finance theory and are practitioner-focused, consistent with the building of themes from the "bottom-up" in constructivist research (Creswell & Plano-Clark, 2018).

Just as there are inherent limitations to quantitative research, a qualitative approach alone would have had certain critical disadvantages for a study of this nature. Specifically, the testing of hypotheses is relatively limited with qualitative approaches. The researchers' bias may have an influence on the interpretation of the results and generalisation thereof would have been limited (Brierley, 2017).

The present study involved the collection and analysis of both qualitative and quantitative data. An interpretivist worldview would not have been appropriate for the entire study which includes testing of hypotheses. Similarly, a positivist approach would not have required the semi-structured analyst interview data.

3.3. Research design

Brierley (2017) posits that researchers are more likely to adopt a mixed methods design if their beliefs are shared with other researchers of the same specialty area. Although the mixed methods research is relatively rare in the research on integrated reporting and equity analysts, there are some instances in which researchers deem the mixed methods approach to be most appropriate.

A mixed approach is adopted in cases where the topic of the study is relatively unexplored. Ihantola and Kihn (2011) use the analogy of an unchartered territory, where mixed methods are recommended where theoretical roadmaps do not yet exist. In these instances, they explain it is important to use several methods to stay on the correct route. Hoffmann and Fieseler (2012 p.142) sought to "explore and identify the widest possible range" of non-financial factors that equity analysts consider when analysing a company. The initial stage of their exploratory study was to conduct semi-structured interviews with analysts. Using the results of their interviews, they created a questionnaire which was distributed to a larger sample of analysts to complete. In this way, the authors were able to establish the direction of the rest of their research, in the absence of extensive prior literature.

Another motivation for a mixed methods approach is when the phenomena that are being explored are not readily quantifiable. These include perceptions of market participants or the influence of heuristics. Hoffmann and Fieseler (2012) wanted to capture the relative importance of non-financial factors to the perceptions of equity analysts. Similarly, Machado and Lima (2021) examined the effect of heuristics on the detail and tone in the analysts' reports. The authors further explain that they wanted to understand how analysts process information. On a similar topic, Ahmad (2020) calls specifically for mixed methods research to understand how heuristics affect investment management activities.

For this study, the choice of research method was also influenced by the choice of research question. This approach is underscored by Creswell and Plano-Clark (2018) and Brierley (2017) who emphasise the importance of the development of research questions which can be answered by integrating the results of quantitative and qualitative research. Qualitative research on analysts' and fund managers' investment decisions has asked "what", "how" and "why" questions. Coleman (2014) asked *why* fund managers rarely use financial decision theory in their practice. Holland (2006) asked *what* the main sources of uncertainty are when making investment decisions. Chaudhury, Sahoo and Dawar (2022) asked *how* buy-side analysts use research from sell-side analysts to make investment decisions. A similar research agenda was pursued by Imam and Spence (2016), albeit with a "what" research question – the authors asked *what* role does sell-side research play in the investment decisions of buy-side analysts. These research questions were exploratory and non-directional, allowing the participants' views to emerge (Creswell & Plano-Clark, 2018).

Hoffmann and Fieseler (2012) use a mixed methods approach to answer their exploratory question of *what* are the non-financial factors that influence equity analysts' perceptions of a company's value. Machado and Lima (2021) ask *how* as they seek to evaluate the effects of heuristics on the detail and tone of analysts' reports. The present research seeks to understand what the effect of integrated report quality is and how report quality and biases affect forecast decisions. They are detailed in the rest of this section with their associated hypotheses.

RQ1: What is the effect of the quality of integrated report information on the market?

Hypotheses associated with this research question are:

H1.a. The quality of information contained in a company's integrated reports has a positive relationship with the quality of analysts' forecasts for that company.

H1.b. The quality of information in a company's integrated reports has a positive relationship with share price performance of that company.

RQ1 and associated hypotheses were approached using quantitative and qualitative methods of analysis. From a quantitative perspective, descriptive statistics and a structural equation model was used. Each hypothesis was associated with a path in the structural model depicted in Figure 12: Structural Equation Model 1. The researcher sought to triangulate the findings of this quantitative analysis with the insights obtained during the qualitative analysis (Creswell & Plano-Clark, 2018). Therefore, the researcher specifically included interview questions relating to the forms of corporate communication used by analysts when formulating their forecasts.

Similarly, both quantitative and qualitative were used to answer the second research questions and test associated hypotheses.

RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias?

H2: Poor quality integrated reports increase analysts' proclivity to behavioural bias.

In order to answer RQ2 and test it's associated hypothesis, it was necessary to perform the analysis at a bias/ heuristic level of granularity. Therefore, sub-hypotheses were generated for each bias (see H2.a to H2.d in Chapter 2: Literature Review). For the quantitative analysis, the hypothesised relationships are depicted in Figure 13: Structural Equation Model 2. For the qualitative analysis, the researcher included open ended questions about the information environment and the types of heuristics (if any) that are used when required information is not contained in company reports.

The third research question focuses on the potential influence of behavioural bias on analysts' forecasts.

RQ3: What is the effect of behavioural biases on analysts' forecast decisions?

H3. The behavioural bias of equity analysts has an effect on the quality of their forecast decisions.

As per the approach with the second research question and set of hypotheses, the analysis required to answer RQ3 was performed at a bias/ heuristic level of granularity and sub-hypotheses were generated for each bias (see H3.a to H3.d in Chapter 2: Literature review). Hypothesised relationships are depicted in Figure 13: Structural Equation Model 2.

Due to the inherent limitations and reductionist potential of quantitative analysis using measurement approximations, the interviews with the analysts were particularly important in answering RQ2 and RQ3. To answer these research questions, open ended questions regarding the influence of factors other than corporate reports, were posed to analysts.

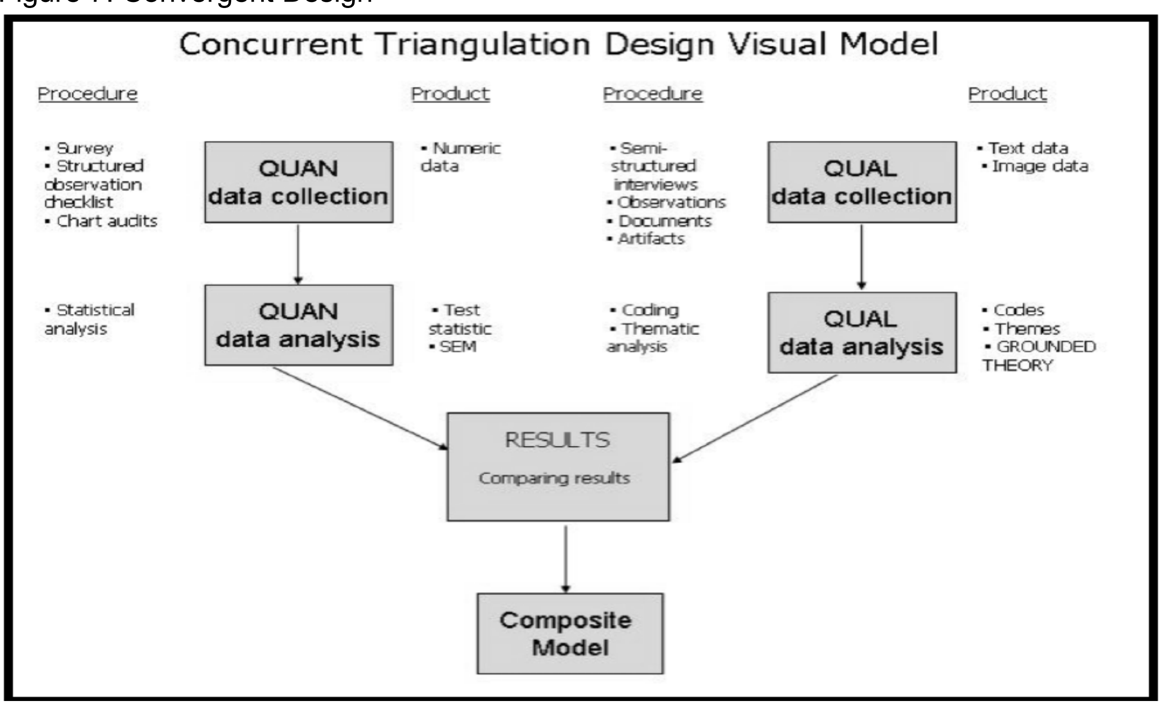
Having decided that the research problem called for a mixed methods design, the next step in the research process, according to Creswell and Plano-Clark (2018), is to choose an appropriate research design. The research design should be aligned to the research paradigm and the reason for mixing. Where a pragmatic paradigm has been adopted, Creswell and Plano-Clark (2018) suggest that a convergent design (also referred to as a "concurrent triangulation design" in earlier versions of Creswell's publications) is chosen. This is because quantitative and qualitative data will be analysed separately and then merged. Both types of data were used to achieve the same research aim, with the quantitative data used to test the hypotheses based on a large number of analyst forecasts and the qualitative data giving insights that are “beneath the numbers” (Horton, Macve & Struyven, 2004).

Another consideration is that of the reason for mixing. A key motivation for the mixing of methods in the present study is to obtain an holistic understanding of the topic and to be able to compare one set of findings to another, for enriched interpretations. Specifically, the quantitative data and analysis in this study was used to test the hypotheses on the influence of integrated reports and behavioural bias on analysts’ share price forecasts. The qualitative data gathered from the semi-structured interviews were used to provide deeper, contextual insights that were not contained in the quantitative data.

Quantitative methods, usually involving measurement approximations, can be reductionist and lack contextual relevance. Qualitative methods, whilst lacking generalisability, allow researchers to provide rich explanations for real-world situations (Creswell & Poth, 2016). To this end, in the current research, each research question is linked to both a quantitative and qualitative method. Therefore, the convergent design was chosen for this study. The convergent design is used when the researcher collects and analyses quantitative and qualitative data separately and then merges the two set of results for comparison.

The design is illustrated in *Figure 7: Convergent Design.* This design guides the structure of the methodology, analysis and results chapters of this study. It is therefore subsequently referred to as the research progress.

Figure 7: Convergent Design



Source: Creswell and Plano-Clark (2018) as adapted in Carmichael (2020)

3.4. Population and Sample

Applying Figure 2 to the current study, Table 3 summarises the quantitative and qualitative data and the research question for which it was required.

Table 3: Data and associated research questions

Data	Research Question/s
Quality scores of the integrated reports per company per year (or per company-year)	RQ1: What is the effect of the quality of integrated report information on the market? RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias?
Share price performance (per company-year)	RQ1: What is the effect of the quality of integrated report information on the market?
Analysts' share price forecasts (per company-year)	RQ1: What is the effect of the quality of integrated report information on the market? RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias? RQ3: What is the effect of behavioural bias on analysts' forecast decisions?
Numeric values representing behavioural biases via measurement approximations and indicator variables (per company year)	RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias? RQ3: What is the effect of behavioural bias on analysts' forecast decisions?
Qualitative data - transcripts from interviews with sell-side equity analysts.	RQ1: What is the effect of the quality of integrated report information on the market? RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias? RQ3: What is the effect of behavioural bias on analysts' forecast decisions? The interviews included questions or conversation guides that addressed each of the research questions. A detailed interview guide, linked to each research question is presented in Table 3 in Section 3.4.1.

3.4.1. Qualitative Data

3.4.1.1. Semi-structured interviews with analysts

Semi-structured interviews provide an in-depth exploration of the lived experiences of practitioners and are the most appropriate means to extract their insights (Roberts, 2020). They enable sense-making through dialogue, thereby allowing researchers to uncover explanations for real-world situations, other than theoretic propositions (Charmaz, 2006).

Interviews were undertaken with 20 participants who were currently employed as sell-side equity analysts or had been employed as sell-side analysts in the past. These types of interviews are common in qualitative literature (Creswell & Poth, 2016) because they provide a dialogic means of making sense of experiences. The technique is becoming increasingly popular amongst qualitative finance researchers too. In the 2023 and 2022 issues of the journal, “Qualitative Research in Financial Markets”, eight studies involved interviews, of which six were semi-structured interviews, one was unstructured and one used focus groups. In a mixed methods study, Horton, Macve and Struyven (2004) found that statistical analysis and interview data were complementary and provided a well-rounded perspective in the study. However, they found that the interviews were “the more valuable part of the research” as the interviews revealed details that were hidden “beneath the numbers” (p. 344).

Interviews included semi-structured, open-ended questions. Semi-structured interviews were considered most appropriate as the questions provide guidance but are sufficiently open-ended to allow flexibility and free flow of responses from participants (Creswell & Creswell, 2017). In interviews with fund managers, Coleman (2014) used broad questions that “allowed deep delving into issues, rather than populate answers to a questionnaire” (p. 229). Furthermore, the interview process enabled further probing and requests for granularity in responses as required; a benefit that would not have existed with a pre-designed survey, the inherent structure of which would have had to constrain the choice of answers (Coleman, 2014).

To qualify for inclusion in this study, participants must be working as a sell-side analyst or must have worked as sell-side equity analysts in the past. The individuals needed to have issued publicly available recommendations and prepared reports containing recommendations for at least one JSE-listed company. A purposive sampling method, combined with a snowballing approach was therefore followed (Creswell & Poth, 2016). The researcher, having worked in a financial institution in the past[7], used her professional networks to obtain the initial participants for the study, as was done by one of the authors of Chaudhury *et al.* (2022). For these six initial participants, contact was made via an email, requesting participation in the study. The email outlined the objectives of the research and provided assurances that interviews and subsequent analysis and presentation would be in accordance with the protocols of the Ethics Committee of the University of the Witwatersrand. The following documents were attached to the email:

1. Participant Information Sheet
2. Participant Consent Form

[7] The researcher had not worked as a sell-side or buy-side analyst but had interacted with such analysts during her time in the financial institution.

3. Ethics Clearance Certificate

An example of an email requesting participation is provided in Appendix H. All six individuals who were contacted as part of the initial sample selection process agreed to participate in the interview.

After each interview with the initial six participants, the researcher requested details of potential participants who met the selection criteria and who would possibly be willing to participate in the study. For this second phase of sample selection, initial contact was made via email or LinkedIn, with a brief introduction from the researcher and an invitation to participate in the study. Over the course of the period during which interviews were conducted, an additional 18 potential participants were contacted. These 18 individuals were referred to the researcher via the initial participants and were selected by the researcher based on the outlier observations identified in Section 4.3.2. Four of the 18 individuals did not respond to the initial introductory message and were not contacted further. Fourteen individuals were therefore interviewed in addition to the six individuals from the first phase of the sample selection process, giving a total of 20 participants. Upon receipt of a response indicating willingness to participate, the introductory email/ LinkedIn message was followed by a more detailed email containing the documentation listed in points 1 to 3.

Interviews were conducted from January 2022 to July 2023. This 19-month period may be regarded as extensive when compared to Atkins and Maroun (2015), where interviews were conducted between May and November 2012. However, it is not unusual when compared to Imam and Spence (2016), who conducted interviews over the 5-year period from 2002 to 2007 and Holland (2006) whose interviews spanned a 3-year period from 1997 to 2000. The extended periods of time between interviews were due to the researcher's and participants' pre-existing commitments, with interviews usually happening a few weeks after initial contact. Most interviews were held between January 2022 and September 2022. In May 2023, the researcher received an unexpected response to an interview request sent in September 2022 via LinkedIn. The potential participant explained that he had experienced an extremely busy few months and apologised for the delayed response. This individual was interviewed in the final interview session in July 2023. The nature of the initial responses provided anecdotal evidence of the time constraints in the environment in which sell-side analysts must perform their duties. The cognitive psychology literature provides evidence of the effect of time pressure on the proclivity for bias (Young, Goodie, Hall & Wu, 2012). A more robust analysis on the effects of time pressure on proclivity for bias is deferred to future research.

Interviews lasted between 45 to 60 minutes, which is slightly longer than the 30-minute semi-structured interviews in Imam and Spence (2016). Interviews were all conducted virtually, via MS Teams. This method was initially chosen due to the restrictions on in-person social interactions as part of the lockdown restrictions due to the COVID-19 pandemic (Republic of South Africa Government, 2020). Once restrictions had eased, the researcher made the option of an in-person interview available to the participants. All participants preferred virtual meetings to minimise the time away from their day-to-day activities, evidence of the videoconferencing interview "compressing the time-space divide" (Khan & MacEachen, 2022, p. 1).

Videoconference interviews (or virtual interviews) have become a popular method of qualitative data collection (Khan & MacEachen, 2022). Although virtual interviews were a mandatory means of communication as a result of COVID-19 lockdown regulations, this type of qualitative data gathering has become increasingly popular. Key benefits include accessibility and affordability. However, poor internet connectivity and dropped calls may affect the quality of the interview. A benefit of qualitative research is that non-verbal gestures can provide richer insights than quantitative data (Creswell & Poth, 2016). Furthermore, in-person meetings may foster a sense of comfort for the participant, enabling a more trusted sharing of insights from the participant (Curasi, 2001; Khan & MacEachen, 2022). The use of the camera function on MS Teams allowed the researcher to observe non-verbal cues and facial expressions of the participants. Bertrand and Bourdeau (2010) explain that a key benefit of virtual interviews is the analysis of body language after the event, strengthening the analysis of the interview data. In this study, only one participant preferred to conduct the interview with their camera switched off.

Further benefits of MS Teams meetings were that they could be easily recorded and transcribed in real time using the software application. Interviews were recorded only once consent was granted by the participants (Roulston & Choi, 2018). All participants agreed to have the interviews recorded and transcribed. The automatic transcription of the meetings enabled the coding of the interview data. Interview transcripts are often sent back to the participants to ensure accuracy of the transcription (Horton, Macve & Struyven, 2004). For the present study, this step was not deemed necessary as the transcriptions captured the responses verbatim. Table 4 below shows a summary of the interviews and participants in this study.

Table 4: Interview Details

Participant Number	Period	Approximate Interview Duration in Minutes	Industry	Years of experience
1	Jan 22	45	Various	4
2	Jan 22	60	Financial	7
3	Jan 22	60	Mining	3
4	Jan 22	60	Telecommunications	8
5	Jan 22	40	Real Estate	5
6	Jan 22	60	Various	14
7	Feb 22	45	Various	12
8	Feb 22	45	Various	10
9	Feb 22	40	Global	6
10	Feb 22	45	Mining	5
11	Mar 22	45	Property	5
12	Apr 22	40	Telecoms	8
13	Apr 22	40	Various	15
14	Apr 22	40	Various	13
15	Apr 22	40	Retail	10
16	Jun 22	45	Telecoms	8
17	Jun 22	45	Technology	5
18	Jun 22	45	Retail	4

Participant Number	Period	Approximate Interview Duration in Minutes	Industry	Years of experience
19	Sep 22	60	Pharmaceuticals	10
20	Jul 23	60	Various	16

Methodological guidance on the appropriate number of participants in qualitative research is varied. This, despite qualitative research being criticised for its lack of rigour by not justifying sample size (Creswell & Poth, 2016). Amongst the considerations proffered for sample size determination are the purpose of the study (Saunders & Townsend, 2016), its scope, purpose and context (Bryman, 2012), its design (Creswell & Plano-Clark, 2018) and most commonly, its epistemological position (Johnson & Onwuegbuzie, 2004; Boddy, 2016; Creswell & Plano-Clark, 2018).

Grounded theory researchers are advised by Creswell and Creswell (2017) to aim for at least 20 interviews. The concept of data saturation, which is the point at which no new information or themes emerge from the data (Creswell & Poth, 2016), is commonly used to justify sample sizes. It appears that whilst guidance on the exact number of participants varies, the principle is that interview data should be gathered until no further new themes emerge (Charmaz, 2006). The sample size can therefore be as low as 12 participants where the population is relatively homogenous (Boddy, 2016).

For constructivist research, Sandelowski (1995) suggests an upper limit of 50 to the number of interviews so that deep, case-specific analysis can be performed. Whilst Boddy (2016) agrees in principle, the author offers their own rule of thumb of 30 interviews, beyond which analysis can be too cumbersome to analyse. Specifically, this upper sample size limitation of 30 interviews could be considered too large for studies focusing on a single market or country. Sandelowski (1995) recommends a sample size of 10 as being sufficient when dealing with an homogenous population.

Sample sizes in the finance research which focuses on individuals involved in the investment process have been varied. Holland (2006) conducted interviews with 40 fund managers across 35 of the 38 largest institutional investors in England, substantiating their sample of participants by representation of the population. Similarly, when Imam and Spence (2016) interviewed 31 sell-side analysts, they supported their sample size by explaining how the sample compared to the population. In particular, the authors cited representation across a variety of companies that the analysts followed (139 companies across five sectors) as well as experience of the analysts, which ranged from three to 16 years. They also considered the value of investments (GBP51bn) for which the sell-side analysts were responsible. The quest for a representative sample to allow for generalisation is consistent with the positivist approach that is common in quantitative research (Boddy, 2016). The round number of interview participants in Holland (2006) further supports the finding of Mason (2010) that a statistically significant proportion of qualitative studies use a sample size which is a multiple of ten, suggesting a premeditated approach to sample size.

The concept of homogeneity of the population appears to be applied, albeit less clearly than population representativeness, in the qualitative research on the investment processes. Authors mention the country and/ or market that is the focus of their study although the discussion on the homogeneity of analysts within that market does not receive as much attention as representation criteria. Holland (2006) and Imam and Spence (2016) focus on analysts in England and interview 40 and 31 analysts respectively. In a South African context, Atkins and Maroun (2015) interviewed 20 participants, all institutional investors and one standard setter. Across four geographic locations, Coleman (2014) interviewed 34 fund managers. Chaudhury *et al.* (2022) focused on the emerging economy of India and interviewed 10 institutional investors. Instead, the sample size of 10 was substantiated using the concept of data saturation – the authors explain that after the 7th interview, there were few additional insights and the marginal returns of subsequent interviews began to diminish.

Being part of a mixed methods approach, the role of qualitative analysis in this study was to provide a depth of understanding (Boddy, 2016), with the breadth being provided in the quantitative analysis. Ultimately, the convergent design in research (see Figure 7) used the different strengths of each method to achieve a single research objective (Creswell & Plano-Clark, 2018). Although the accompanying quantitative analysis required large sample sizes, as explained in Section 3.4.2, the purpose of the qualitative analysis was different from studies in which insights from qualitative data are used to develop quantitative measurement instruments such as questionnaires (Hoffmann & Fieseler, 2012). In planning the study, the researcher applied a pre-meditated approach to sample size estimates (as observed by Mason, 2010) to ensure that the study would be feasible. Creswell & Creswell (2018) suggest that the number of participants should be determined using the qualitative design being used or the concept of saturation. They suggest that researchers may stop gathering data when no new insights emerge – i.e. data saturation is reached. Although the concept of data saturation was developed for grounded theory studies, it can be applied to any study that uses interview data (Marshall *et al.*, 2013). In the present study, no new insights emerged after the 12th interview. However, in order to ensure that views were obtained across a variety of industries, further interviews were conducted.

For this study, the flexibility of the semi-structured approach outweighed the limitations on statistical analysis of the interview data (Horton, Macve & Struyven, 2004), especially since the quantitative analysis had been conducted using other measurement approximations in the structural equation model. Interviews were semi- structured, enabling the gathering of rich insights to understand the complexities of practice (Coleman, 2014) as the researcher was able to further probe participants' responses where required (Horton, Macve & Struyven, 2004). Although the researcher prepared questions to guide the interview, as suggested by Creswell and Creswell (2018), the interviews were only semi-structured. Deviations in terms of sequence of questions and posing of follow-up questions allowed the researcher to gather rich context from the participants' responses (Saunders & Townsend, 2016). Participants were encouraged to speak freely in response to the questions and they were not interrupted. They discussed their personal experiences, with many participants sharing their experiences of failure, when their expectations of companies were incorrect. This type of sharing was particularly valuable for the understanding of reasons for inaccurate forecasts.

3.4.1.2. Research Instrument

Qualitative interviewing requires the interviewer to be well-versed in the topic/s covered in the interviews. In addition, the interviewer must be familiar with how to produce knowledge through conversation (Brinkmann & Kvale, 2005). For this research, the implications of these criteria were that the interview themes needed to be sound in terms of the discipline-specific literature and they had to conform to standards of methodological rigour. These criteria involving discipline-specific theoretical frameworks and methodological thoroughness were considered in the development of an interview guide.

Roberts (2020) explains that interview guides are useful to ensure that a protocol is followed in research that uses human participants. However, these guides need not include the exact wording of questions, which need to be sufficiently open-ended and tailored according to the dynamics of each specific interview. It is therefore sufficient for interview guides to contain an outline of topics or themes that will be addressed in the interview (Rubin & Rubin, 2012; Brinkmann & Kvale, 2005).

Creswell and Poth (2016) advise that researchers should ask succinct, specific, non-leading open-ended questions that are not unrelated to the research objective. In addition, researchers should avoid asking questions that validate their own expectations. In developing the interview guide, the researcher was guided by prior research which suggests that the purpose of a qualitative interview is not to ensure that the questions are perfectly answered but rather to listen to the stories of participants so as to understand how their experiences unfolded and the meanings that they associate with those experiences (Creswell & Poth, 2016). The number of questions was deliberately limited so there would be sufficient time for further probing or slight deviations from the script, in line with the semi-structured nature of the interviews. Brinkmann and Kvale (2005) stress the importance of the objective of the research and its link to interview questions. In order to ensure that the researcher did not deviate from the research topic, each research question was linked to specific interview questions/ themes. Specifically, the researcher considered each aspect of the research questions, particularly each behavioural bias and attempted to develop a question to address each bias as far as possible (Rubin & Rubin, 2012). In some instances, it was possible to develop such specific questions/ prompts to address a specific bias. For example, to gauge the potential influence of loss aversion on forecasts, the researcher enquired about the circumstances in which recommendations would be downgraded versus the circumstances in which recommendations would be upgraded. However, prompts about the participants experiences with inaccurate versus accurate forecasts were relatively more open-ended and intended to provide insights into several biases such as overconfidence and availability.

The planned first question was broad, with participants being able to respond to the opening question by providing a tour (Rubin & Rubin, 2012) of the processes involved in arriving at their forecasts. Subsequent questions focused on specific aspects of the processes, as is common in a grounded theory study (Roberts, 2020).

The researcher’s interview questions were informed by insights from prior literature, particularly on behavioural biases in the context of analysts. The questions were developed primarily with reference to the existing literature on report quality and behavioural bias and heuristics. A limitation of interviews in any study is that participants (intentionally or unintentionally) may provide the views that they think they should have or that they want the researcher to think they have, rather than their honest opinions (Horton *et al.*, 2004). For this study, the researcher attempted to reduce the likelihood of this situation by providing assurances of confidentiality and encouraging participants to be open about their opinions. In addition, the relative consistency in responses across participants provided some assurance of the validity of responses (Horton *et al.*, 2004).

A related limitation of interviews in a study on behavioural bias is the futility of asking participants whether behavioural bias affected/ affects their decision-making. The likely answer would be “no”. In addition, participants may not be familiar with the definitions of certain biases and may incorrectly attribute or fail to attribute their decisions to bias or heuristics. The development of questions for interviews was particularly important to ensure that information on biases could be efficiently and effectively collected from the interviews.

To this end, the researcher conducted pilot studies on two participants, one of whom is an academic and practicing Chartered Psychologist, with experience in cognitive behavioural therapy. Pilot studies are useful as they provide the opportunity to identify instances where questions are not clear, insufficient or too complicated (Roberts, 2020). The second participant for the pilot study was employed in a financial institution and had experience in its Investor Relations division. The participant had therefore worked with sell and buy side analysts. The focus of the pilot study with this participant was to determine whether the questions were not irrelevant to the realities of practice as a sell-side equity analyst. The two participants in the pilot study were deliberately chosen for their specific skill set and familiarity with the research topics; albeit from different perspectives.

The Chartered Psychologist was chosen for their ability to provide a perspective on the types of responses that would likely be received by individual participants, when questioned about their experiences or thinking processes. They provided a view on whether the questions were phrased in a manner most conducive to extracting information about the judgement and potential bias that is being assessed. This participant also provided feedback on whether any questions were leading and likely to elicit an obvious or convenient response, especially since the researchers would have more knowledge of the research themes than the participants.

The pilot study revealed that the interview questions could potentially be covered relatively quickly, in approximately 25 minutes. This was attributed to the possibility that none of the participants of the pilot study were currently working as sell-side analysts and may therefore have omitted certain aspects of the role. Another possibility was that certain questions could be answered with very specific responses relating to the procedures followed by the analysts. On formulating questions that are focused on the research aim whist being sufficiently non-leading, Rubin and Rubin (2012) suggest that researchers ask about highlights, turning points and comparisons to elicit rich, vivid and detailed responses. Following the pilot study, and with this suggestion as a guide, the questionnaire was adjusted to be more open ended. Specifically, the researcher asked participants to share their experiences of arriving at a relatively accurate forecast. This was followed by the request to share their experience of arriving at a relatively inaccurate forecast.

In addition, the order of certain questions was changed. The first question was deliberately broad and simple to allow the participant to feel comfortable in the interview, and to share information that came easily to them (Creswell & Plano-Clark, 2018). According to the pilot study feedback from the participant who had worked with sell-side analysts, responses to the opening question were likely to include a description of the sources of information used to inform forecasts. The question relating to the reliability of the various sources of information was therefore covered immediately after the first question (and any related probing, depending on responses to the first question).

In accordance with the semi-structured nature of the interviews, the researcher set out to ensure that all themes (biases in the present study) were covered. Although questions were scripted to ensure consistency across all interviews, the exact wording of the questions varied depending on the participant's responses.

A summary of the prepared interview questions/ guidelines is presented in Table 5 below:

Table 5: Interview Guide

Ref.	**Topic to cover**	**Link to Research Aim/ Research Question**	**Precedent/ Reason for asking the question**
1	Tasks performed when analysing a company to provide a forecast or recommendation.	"Tour" question [All RQ's]	Creswell and Creswell (2017) (adapted) This opening question is asked to set the interviewee at ease. This is a question where participants can speak about themselves in a relaxed manner.
2	Most important source of information used	Use of integrated reports and investor scepticism [RQ1]	The research from Barth *et al.* (2017) and Eccles *et al.* (2019) hypothesises that higher integrated report quality improves forecast accuracy. Pistoni *et al.* (2018) find that the quality of information in integrated reports does not always support investment decision-making. Question 2 and Question 3 seek to establish the extent to which information in the integrated reports is used and the reliance that is placed thereon.
3	Sources of uncertainty when forecasting share price performance	Use of integrated reports and investor scepticism [All RQ's]	The research from Barth *et al.* (2017) and Eccles *et al.* (2019) hypothesises that higher integrated report quality improves forecast accuracy. Pistoni *et al.*

Ref.	Topic to cover	Link to Research Aim/ Research Question	Precedent/ Reason for asking the question
			(2018) find that the quality of information in integrated reports does not always support investment decision-making.
4	Approach when information from the analyst's own models is incongruent with information reported by the company/ in the public domain.	Overconfidence [RQ2 and RQ3]	Hilary and Menzly (2006), Barber and Odean (2001) Prior research suggests that overconfident individuals overweight their private information. However, in the current context, the overweighting of private information could be due to poor quality of public information.
5	Impact of audit failures/ accounting irregularities	Use of integrated reports and investor scepticism [All RQ's]	The purpose of this question is to determine the impact of audit failures on the reliance that analysts place on the information in the integrated reports. It starts the conversation regarding the potential increased use of judgment, given the possible reduced reliance on integrated reports.
6	Reflection on achieving a relatively accurate forecast / recommendation	All biases [RQ 2 and RQ3]	Olaf Stotz & Rudiger von Nitzsch (2005): A manifestation of overconfidence with regards to earnings is the perception of increased control.
7	Reflection on achieving a relatively inaccurate forecast/ recommendation.	All biases [RQ 2 and RQ3]	
8	Key indicators of future performance of a company	All biases [RQ 2 and RQ3]	Shefrin & Statman, (1985); Mokoaleli-Mokoteli *et al.*, (2009); Ahmed & Flint (2020) Various researchers find evidence of the market view that good shares imply good company

Ref.	Topic to cover	Link to Research Aim/ Research Question	Precedent/ Reason for asking the question
			fundamentals and past stock performance is representative of future performance. The purpose of this question is to determine to what extent the analysts employ the representativeness heuristic to predict the future performance of shares.
9	Reasonability checks for forecasts/ recommendations	Herding [RQ 2 and RQ3]	Leece & White (2017); Benkraiem, Bouattour, Galariotis & Miloudi (2019) Analysts tend to exhibit a greater degree of herd behaviour in environments where the quality of information is lower. In these environments, the more capable analysts act first and the less capable analysts follow
10	Effect of institutional ownership/ media coverage/ greater availability of information	Availability/ Anchoring/ Familiarity [RQ 2 and RQ3]	Jang & Ho (2020) In an evaluation of the quality of analysts' forecasts, the proxy for familiarity was the percentage institutional ownership in any of the selected firms. It was assumed that the higher level of institutional ownership suggests increased monitoring and access to information.
11	Reasons for and frequency of upward revisions of forecasts Reasons for and frequency of downward revisions of forecasts	Loss Aversion [RQ 2 and RQ3]	Asquith *et al.* (2005) The quantum of increase in the earnings of firms added to a strong buy was less than the quantum of decrease of shares added to the strong sell list. This implies that the increase in stock price before it was recommended as a "buy" would be less than the decrease in stock price before a "sell" was recommended.

3.4.1.3. Format of interviews

Meetings with potential participants were scheduled in advance, after introductory emails and participants agreeing to meet. Potential participants were advised that the interview would be conducted during the scheduled session, if they agreed to participate in the study. The scheduled meetings began with more detailed personal introductions, if the potential participants had not met the researcher in the past. These less formal introductions are useful in putting research participants at ease (Roberts, 2020). Following the introductions, the researcher made use of the screen-sharing functionality in MS Teams to share the Participant Information sheet (Appendix J) and the Consent Form (Appendix K).

Potential participants were assured of the confidentiality of the information discussed in the interviews. This was particularly important since sell-side equity analysts are incentivized to provide relevant and up-to-date company insights to potential clients of their employers. The researcher further assured the participants that the insights shared would be used for research purposes only. Consent to participate in the study was forthcoming from all participants, who further agreed to having the interviews recorded.

The interview guides were not shared with the participants before the interview unless specifically requested. This was a deliberate attempt by the researcher to ensure that the participants provided authentic instead of pre-prepared responses. Participant 4 specifically requested an indication of the topics to be discussed in the interview, so that he could share them with his employer before proceeding with the interview. The researcher obliged and the interview guide was provided, along with assurances of confidentiality and anonymity. The researcher further explained that there would be no expectations regarding “correct” responses; instead the focus would be on descriptions of the participant’s experiences in practice (Roberts, 2020). Subsequently, the participant explained that his employer felt that no clearance would be required from their compliance department due to the nature of the questions being asked.

Interviews then began with the opening, “tour” question (Rubin & Rubin, 2012). The broad nature of the question allowed the participants to answer freely and emphasis aspects of their experience that they considered important (Roberts, 2020). The remaining questions followed from the introductory question, allowing free flow of participants’ ideas. The researcher attempted as far as possible to alter the order of topics to be discussed so that the interviews were more conversational and did not feel like an interrogation (Rubin & Rubin, 2012).

3.4.1.4. Ethical Considerations

Ensuring the protection of rights of human research participants is of utmost importance in any study (Oliver, 2010). Prior to conducting this study, the researcher applied for ethics approval for non-medical research from the University of the Witwatersrand’s Human Research Ethics Committee. An online ethics application was submitted to the Committee, along with the approved research proposal, the Participant Information Sheet (Appendix J) and the Participant Consent Sheet (Appendix K). The Committee considered the application on 26 November 2021 and issued an Ethics Clearance Certificate (Appendix I), with expiry date 19 December 2024.

In accordance with the protocols stipulated in the application forms to the Ethics Committee, the researcher distributed the Ethics Clearance Certificate, Participant Information Sheet, and Consent Forms to the participants prior to each interview. In addition, the researcher emphasised that all data which was collected through interviews would be encrypted and stored in password protected files on a University-owned computer. Participants were assured that company names and other information that might compromise their anonymity would be redacted in the study. One participant further requested the interview guide, for submission to the Compliance Department of their workplace. The researcher obliged and assured the participant that the interview would be for research purposes only and that all responses would be anonymised in the report and any resulting publications. The participant was also assured that there would be no correct or incorrect responses to the questions in the interview. The participant responded that the Compliance Department at his workplace had agreed that no specific permission would be required from them. All participants provided consent prior to the interview.

3.4.2. Quantitative Data

For the quantitative analysis, the unit of analysis is the company-year. This structure was followed as integrated report quality scores are allocated on this basis. Therefore, the quality of analysts' forecasts was also measured in relation to each company-year.

For RQ1, the population was therefore integrated reports issued by JSE-listed companies. The sample comprised the companies that were rated in the annual EY Excellence in Integrated Reporting Awards. The data therefore includes scores representing the quality of the integrated reports (independent variable). For each company, the associated analyst forecasts and share price performances were used as dependent variables. Each company had to have at least three analysts following them, so that the dispersion in analyst forecast and other measurement proxies could be meaningful.

RQ2 and RQ3 incorporated the effect of behavioural biases. Therefore, in addition to the data used for RQ1, forecast data was used to calculate measurement indicators for each bias. The behavioural biases cannot be directly measured and are therefore latent constructs. In order to achieve construct reliability in this study's analysis, each bias was measured using several indicators.

Empirical research on analysts' forecasts tends to include a large number of forecasts over several periods. The regression analysis of Hong and Kubik (2003) included analysts forecasts from 1983 to 2000 and extended across 619 brokerage houses and 8441 firms.

The required sample size is determined by the analysis technique to be used. To empirically analyse the effect of integrated report quality and behavioural bias on forecast decision quality, a structural equation model (SEM) was used. SEM is a methodology that is used for large sample sizes, with 300 observations used as a rule of thumb for a reliable analysis (Kline, 2015). Kline (2015) further connects sample size in SEM to the number of parameters and recommends that the ratio of observations to estimated parameters (N:q) be used as a guideline. Whilst the recommended ratio is 20 observations for each parameter, this ratio drops to 5 observations per parameter in Bentler and Chou (1987). Westland (2010) highlights the limitations of these rules of thumb and suggests using several additional variables to calculate sample size. The author developed two algorithms to compute the lower bounds on sample size – the first being a function of the ratio of indicator variables to latent variables, and the second being a function of minimum effect, power and significance. As an initial indication of the required sample size for this study, we estimate 10 observations (Nunnally, 1994) per the higher of the number of quality variables and bias variables[8] as the lower bound of the sample size.

The use of large sample sizes is common in the research on analyst forecasts. In Asquith *et al.* (2005), the researchers used 1126 analyst reports, written by 56 different analysts, covering 46 different countries. Ahmed and Flint (2020) analysed 43 086 price forecasts over a period of 15 years. A study using SEM in an accounting context, with company fundamental data, was that of Ittner *et al.* (1997). Their analysis used cross sectional latent variable regression analysis of data from 317 firms for a one-year period. In comparison, our analysis comprises 342 company-years (Table 6) and 316 analysts (Table 8).

EY, a big four audit firm, conducts annual reviews of integrated reports for their “Excellence in Integrated Reporting” awards. Further discussion on these awards is contained in the literature review of this study. EY shared their scores of integrated report quality with the researcher, for use in this research project. An email requesting the scores was sent to the Partner at EY who was responsible for the co-ordination of the awards processes. The partner agreed to share the scores and they were then provided, via email to the researcher by one of the expert adjudicators. Scores were provided in MS Excel workbooks. The scores provided covered the 6-year period from 2016 to 2021. Scores were based on the integrated reports of companies in the immediately preceding year. For example, integrated reports for the year ending 31 December 2015 would be assessed in 2016 and the scores would be published in 2016.Of these companies, we excluded those with thin analyst following and missing score data for any of the six years in the period of analysis. This left 67 companies. Tables 6 and 7 detail the sample of companies and analyst recommendations used in the final statistical analysis.

Table 6: Sample Selection – Companies

Sample Selection	**Companies**
EY observations	126
Thin analyst coverage	(26)
Missing score data	(33)
Sub-total	67
Unknown integrated report release date	(10)
Total Companies	57
Total Company years	**342**
Industry Composition – company years	
Financials	108
Consumer goods and services	84
Health care	30
Telecommunications	18
Basic Materials	78

[8] The same companies were used in Part 1 and Part 2. Hence, the number of observations depends on both the quality variables and the bias variables.

Industrials	18
Oil and Gas	6
Total Company years	**342**

Barth *et al.* (2017) also created a proxy for quality based on scores for various criteria. Their research used the secondary data from audit firm EY, which evaluates integrated reporting quality for their annual Excellence in Integrated Reporting Awards. This research also uses data from the EY IR quality awards. Quality scores for the period from 2016 to 2021 was provided by EY and the adjudicators, upon request from the researcher. Quality scores for each of three categories of quality were used in the measurement model for IRQ or integrated report quality.

Prior studies relied solely on the analysis of the reports and forecasts. They did not include interviews with the analysts to compare the results of their quantitative analyses. The purpose of a mixed methods design, as proposed, is to use the qualitative date to provide more depth and insights into the qualitative results (Creswell & Creswell, 2017). Financial analysts are key users of financial information and their interpretations are an important example of the manner in which information is used. Their recommendations are therefore the basis of analysis for the quantitative analysis of how corporate information is used. The data on the use of information therefore comprised analyst recommendations (quantitative) as well as interviews with analysts (qualitative).

As discussed in Section 3.5.2, Forecast Error in Model 1 (SM1) was measured as the standard deviation of the forecasts of all analysts following a company. This meant that any firms with less than two analyst recommendations in any single year were excluded from the analysis for that year. In addition to the 26 companies which were excluded due to thin analyst coverage per Table 6, the seven company-years detailed in Table 7 were excluded. These observations related to specific years in which recommendations from more than one analyst were not available.

Table 7: Company-years excluded due to less than two recommendations issued

Company	**Year**
AECI Limited	2020
African Rainbow Minerals Limited	2020
Coronation Fund Managers Limited	2019
Fortress Real Estate Investment	2019
JSE Limited	2017
Liberty Holdings Limited	2020
Netcare Limited	2019

This left 335 analysts and 2208 recommendations over the period 2017 to 2022. This period was chosen to align with the period for which the integrated repot quality scores were provided.

Table 8: Sample Selection – Analysts and Recommendations for the entire sample period[9]

Number of analysts	316
Total number of recommendations	2208
Number of analyst employers (asset managers)	60

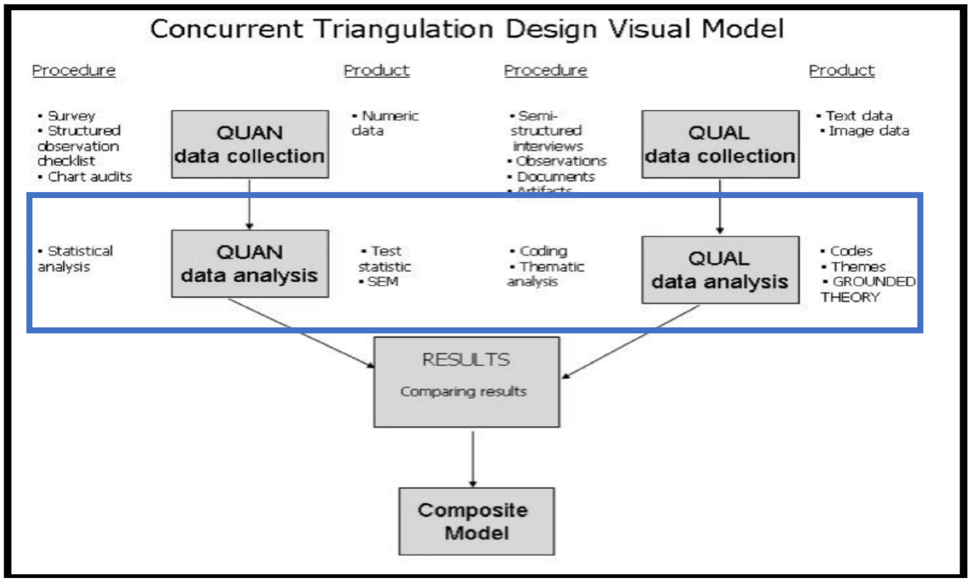
The most followed companies were Anheuser-Busch InBev (ANH) in 2017, with 28 recommendations issued and British American Tobacco (BTI) in 2018, with 20 recommendations issued. On average, 7.92 recommendations were issued for each firm in each year. In 2016, ANH acquired SABMilller for USD 100 billion, in one of the largest mergers in the history of the South African market (ABI, 2016). In 2018, the value of BTI's shares decreased by more than 50% due to legislation that would restrict the amount of nicotine in traditional cigarettes (The Value Portfolio, 2019). This information provides anecdotal indications of the factors that drive analyst following. When large companies are involved in significant merger and acquisition activity, or when their share prices experience significant movements, they attract the attention of analysts who have potentially identified arbitrage opportunities.

3.5. Analysis

Having discussed the quantitative and qualitative data used in this study, Section 3.5. focuses on the analysis of the respective types of data. As in Figure 7: Convergent Design, the qualitative and quantitative data were analysed separately, using the technique most suitable for that type of data, to achieve the research objectives. The analysis is structured to first present the qualitative analysis. Although presented subsequent to the qualitative analysis, the quantitative analysis occurred concurrently, as in any convergent design. This concurrent analysis enables the corroboration of interview themes with the statistical evidence and vice versa. Results are discussed and compared in Chapter 4.

Figure 7: Convergent Design

[9] This table contains the number of analysts, recommendations and asset managers for the period from 2016 to 2021. Details of the number of analysts and asset managers per year is provided in Table 11 to illustrate a theme that emerged during the interview process of this research.



Source: Creswell and Plano-Clark (2018) as adapted in Carmichael (2020)

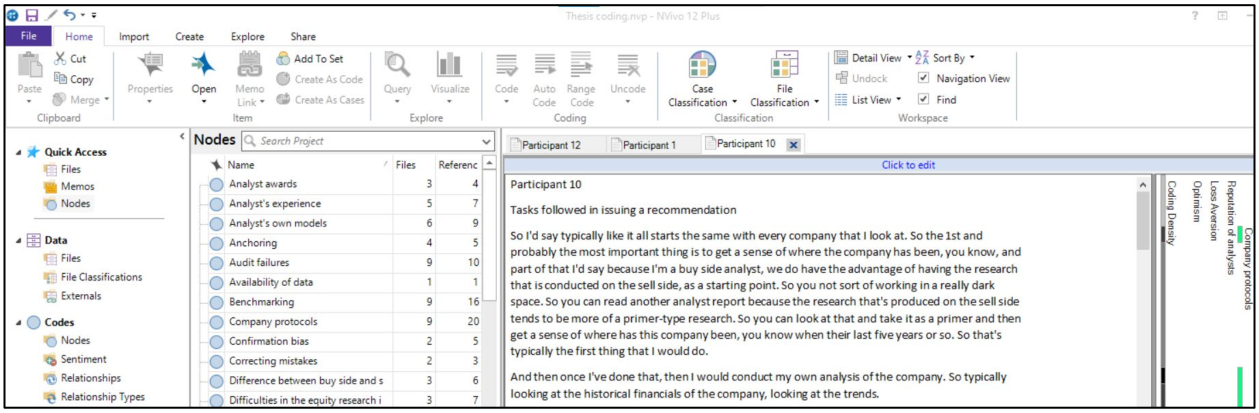
3.5.1. Qualitative Data Analysis

After each interview, the transcripts generated from MS Teams were cleaned and transferred to MS Excel. The cleaning of the interview transcripts was necessary as the voice-to-text functionality of MS Teams did not account for variations in pronunciation of several words. For example, “sustainability of the model’ was transcribed as “stain ability of the model”. There was also unintentional repetition of words by participants as they thought aloud about the questions and their responses e.g. “So, so, there’s, there’s a lot of things…”. During this phase of cleaning of the transcripts, the video recordings were also used to ensure that the participants exact words were recorded (excluding pauses and irrelevant words such as “uhm, err, etc.).

Saldana (2021) suggests that a codebook be used to document and categorise codes from the various interview transcripts. The author also encourages the use of data analysis platforms such as Atlas.ti for coding and cataloguing of qualitative sources. For this research, NVivo analysis software was used as a tool to enable efficient and reliable analysis of the interview transcripts. NVivo is a qualitative data analysis software programme that facilitates the systematic analysis of qualitative data (Jackson & Bazeley, 2019). Although NVivo mimics manual strategies of analysing qualitative data, it increases the efficiency of arranging and coding the data. For this research, NVivo was particularly useful during the writing up of the results, as specific quotations from interview participants could be easily accessed. Jackson and Bazeley (2019) explain that NVivo’s tools can enable different forms of analysis of qualitative data, beyond coding. For this research, word clouds were generated to obtain a single view of the data in all the transcripts. In addition, transcripts of participants could be compared to identify similarities, which could generate further insights. The coding process is detailed in the rest of this section.

Figure 8 shows an extract of the project layout in NVivo, for the first coding cycle. For this project, the “Files” were the interview transcripts, while the codes, sub-codes and categories were captured in “Nodes”.

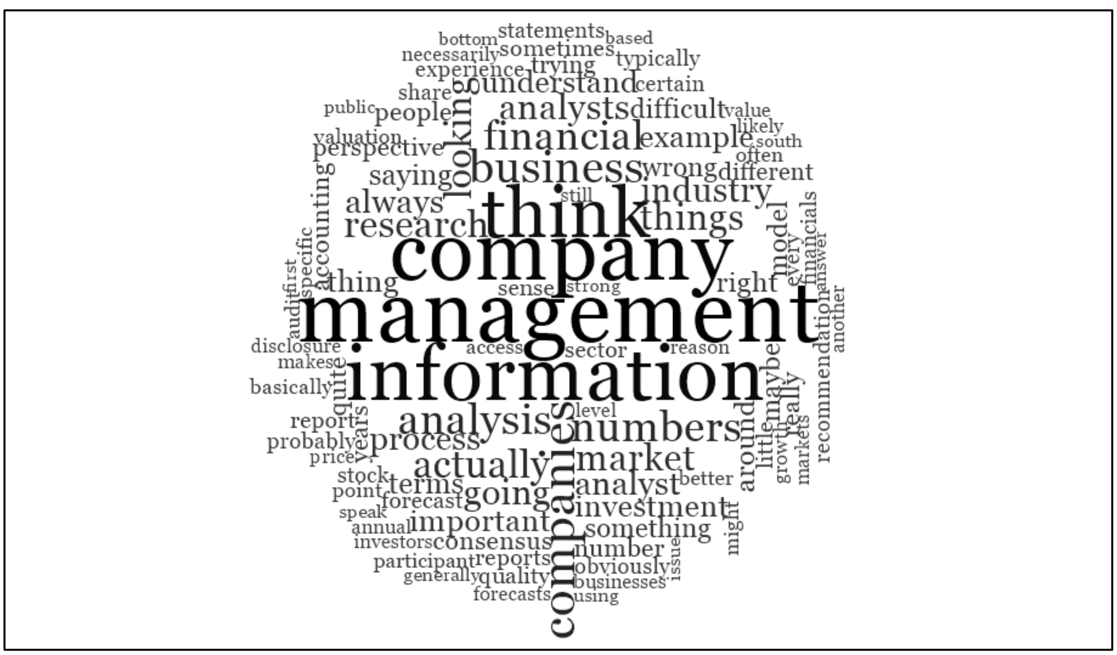
Figure 8: Structure of the project in NVivo



Source: Author's own, created in NVivo.

The "word cloud" functionality of NVivo was used to generate a word cloud from a document containing all interview transcripts. The word cloud is based on frequency of words and excludes all words that are less than four letters long.

Figure 9: Word Cloud from interview transcripts

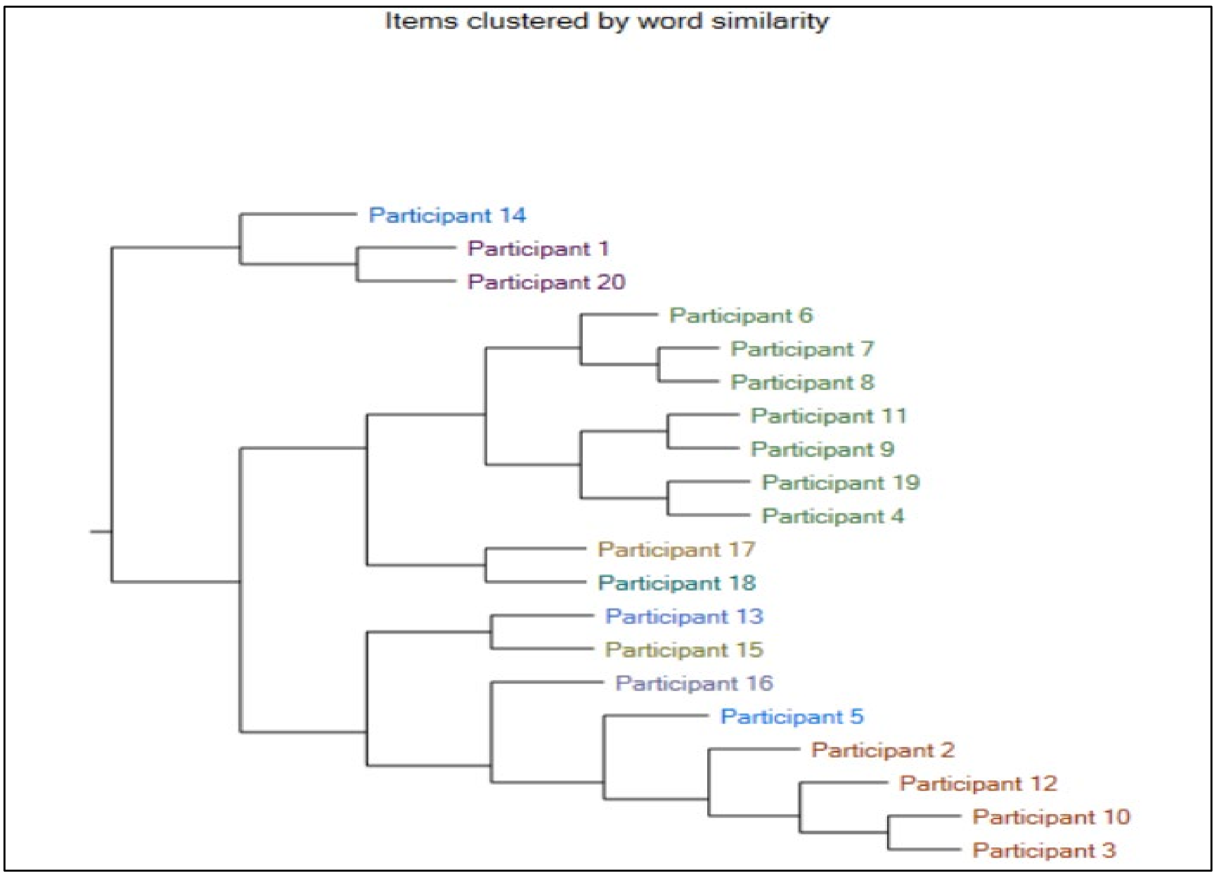


Source: Author's own, created in NVivo.

The word cloud provides a "bird's eye view" of the data contained in the interview transcripts. It shows that the word that was mentioned most frequently was "management", referring to the management of the companies that the analysts cover. From a high-level analysis of the interview transcripts, one of the main sources of information that analysts use when developing their recommendations is discussions with senior management teams or Investor Relations teams from the companies that they cover.

Further descriptive diagrams were generated in NVivo to gain a different perspective on the interview transcripts. Of interest was a cluster analysis dendrogram (Figure 10) which depicts similarities between transcripts. The researcher recognised that, amongst others, there were similarities between the interview transcripts between Participants 6 and 7 and Participants 17 and 18. These pairs of interviews were with analysts from the same financial institution. There were, however, differences in the sectors that these analysts covered. This preliminary view of the interview data appears to indicate that established protocols within investment houses influences the manner in which sell-side analysts behave and think about their forecasts. There also seemed to be a trend of similarity between analysts with similar years of experience (Participants 9 and 11 and Participants 19 and 4), possibly indicating that analysts' experience influences the behaviour and thinking processes of analysts.

Figure 10: Cluster Analysis Dendrogram from interview transcripts



Source: Author's own, created in NVivo.

3.5.1.2. A pragmatic approach to the analysis of interview data

The method of coding of interview data can vary according to the philosophic paradigm that is adopted in a particular study. Researchers may also choose between a deductive approach, where codes and categories are derived from previous literature and an inductive approach, where the themes emerge from the data itself (Creswell & Plano-Clark, 2018). For example, the coding process for a grounded theory study would typically involve focused, axial and theoretical coding (Saldana, 2021). An inductive approach may be most appropriate for a grounded theory study.

In the present mixed method, convergent design study, there is a mixing of methods to enhance reliability of findings. Specifically, the quantitative analysis provided results based on a large sample size, lending themselves relatively better to generalisation than the qualitative results. The latter were used to provide context and deeper insights to answer the research questions. The development and testing of hypotheses in this study is in line with a positivist approach. Yet, the exploration of the work of the sell-side analyst and the situations which may increase proclivity to bias, was more consistent with an interpretivist paradigm. Therefore, whilst a purely inductive method of coding would have been appropriate for certain aspects of the study, it would have been at odds with the pre-conceived starting points and use of existing theories and frameworks in relation to the behavioural biases (Ramanadhan, Revette, Lee & Aveling, 2021).

There is a growing strand of research that bemoans the quest for a single ideal approach to qualitative analysis as limiting necessary adaptations and innovations in methods (Brierley, 2017). Ramanadhan *et al.* (2021) argue that there is no single correct method of approaching qualitative research. In fact, even grounded theory studies are diverse in their approaches and procedures.

Ramanadhan *et al.* (2021) suggest a pragmatic approach to analysing qualitative data, especially when the research is practice-driven. They suggest strategically borrowing approaches from more established traditional forms of qualitative research. However, they caution against combinations that render the study internally incoherent. Similarly, whilst Brierley (2017) promoted pragmatism as an approach that considers “what works”, they issue the qualification that this does not means that “anything goes”. In other words, the chosen method/s of analysis should still ensure alignment between the research question, data collection and analysis. Therefore, the mixing and matching of approaches must occur in a coherent, credible manner.

For this research, a combination of inductive and deductive coding (Brierley, 2017; Ramanadhan *et al.*, 2021) was considered most appropriate to answer the study’s research questions. Brierley (2017) explains that whilst quantitative and qualitative research generate insights using deductive and inductive approaches respectively, within the pragmatic approach, the researcher relies on abduction to move between deduction and induction.

The present study’s research questions lend themselves to a deductive form of coding, especially given the development of hypotheses and extensive reliance on existing theories to do so. Specifically, there is a well-established body of literature that considers behavioural biases and heuristics in the context of capital markets (Tversky & Kahneman, 1974). In addition, the proclivity of analysts, specifically, to these biases has also been considered in several international equity markets (see for example, De Bondt and Thaler, 1990; Leece and White, 2017; Jang and Ho, 2020). However, it is equally important in this research to not only explain the interview data that was consistent with the identified themes but also explore the “outlier” responses. With the objective of this study being to understand the influence of integrated reporting and behavioural bias/ heuristics on analysts’ forecasts, it would have been remiss of the researcher to ignore any divergent reasons for behavioural bias/ heuristics or other unexpected themes that emerged from the interviews. The purpose of incorporating inductive coding methods was to ensure that these divergent cases were not ignored. These cases may contain richer insights which are sought-after from qualitative research.

These richer insights are particularly valuable because of the lacuna of research on analysts in the context of the South African equity capital market. The South African economy is classified as an emerging market. However, it differs from other emerging markets where information flows and corporate governance standards may impact efficiency. In the South African market, integrated reporting is effectively mandatory for JSE- listed companies. It is therefore plausible that themes that have not been covered in prior research may emerge in the context of the South African market. Inductive approaches are particularly valuable here, as they allow the researcher to incorporate themes that were unanticipated from prior research (Saldana, 2021).

Saldana (2021) encourages researchers to show clearly how they used their data to generate insights. To this end, the discussion in the rest of this section describes how the analysis was structured and how the codes were generated from the interview transcripts. The procedure is consistent with the approach suggested by Miles, Huberman and Saldana (2021) for mixed methods research and has also been found to be effective in research that incorporates the view of practitioners (Ramanadhan *et al.*, 2021).

Open coding was employed for the first cycle of coding. Specifically, a coding framework was created using eclectic coding, a coding method whereby the researcher uses a combination of first cycle coding methods. This method is applicable as an initial, exploratory analysis technique for interview data. A combination of descriptive and process coding methods were used (Saldana, 2021). A descriptive code assigns a label or a short phrase (often a noun) to categorise an extract of qualitative data. For this study, the researcher used descriptive codes to disaggregate responses to the interview questions. In some instances, more than one descriptive code was assigned to a particular phrase. For example, the following phrase from the interview transcript of Participant 20 was coded as “Analyst awards” and “Industry analysis”.

*One of our best analysts, ****, contributed a lot to the win because he has excellent industry and sector knowledge.*

Process coding is used to represent action conveyed by the data. It is appropriate for research regarding the actions of participants and the documentation of routines (Saldana, 2021). A large portion of the discussion in the interviews centred around the processes and procedures involved in the formulation of a recommendation (and the participant’s reflection of their own experiences). For these responses, process coding was particularly useful as a first cycle coding method. As with the descriptive codes, the researcher sometimes used more than one process code for a specific phrase in the participant’s responses. The following are examples of participant responses with assigned process codes.

Participant 1:

The issue with all financials is that there is no clear uniformity especially in the way that the assets are valued. That’s why we come back to the technical analysis.

This response from Participant 1 was coded as “Performing fundamental and technical analysis”

Participant 3:

I don't just …. stick with my numbers. I go and look at the broker consensus.

This response from Participant 3 was coded as “Benchmarking”.

A list of codes from the first cycle coding process is contained in Table 9. Inductive coding was used and ideas were allowed to emerge from the data, as described in earlier paragraphs of this section.

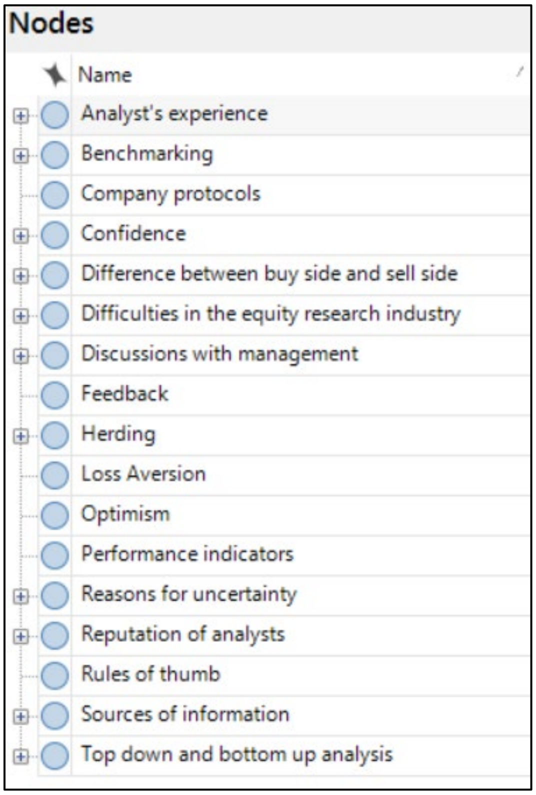
Table 9: First cycle codes

Code		
Analyst awards	Feedback on mistakes	Optimism
Analyst's experience	Fundamental and technical analysis	Overconfidence
Analyst's own models	Herding	Problems with accounting info
Audit failures	Humility	Qualitative analysis
Availability of data	Indicators of performance	Uncertainty
Benchmarking	Industry analysis	Relationship with clients
Company protocols	Institutional ownership	Reputation of analysts
Checking	Loss Aversion	Rules of thumb
Correcting mistakes	Management dominance	Sector expertise
Difference between buy side and sell-side	Market liquidity and participation	Sources of information
Difficulties in the equity research industry	Marketing the research	Straying from the pack
Discussions with management	Most reliable source of information	Top down and bottom-up analysis

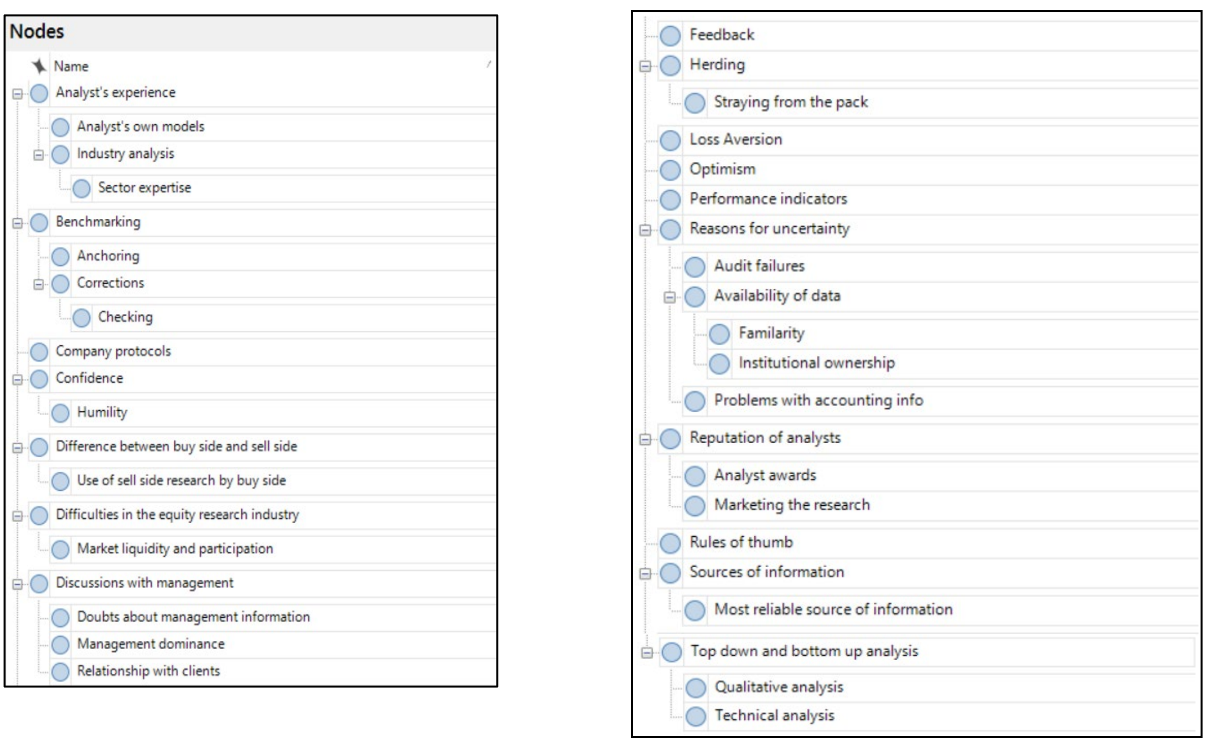
The second cycle of coding used the established coding framework as well as the prior literature to create both deductive and inductive codes. These codes are presented in Figure 11. They were applied to all the interview transcripts. Once the second cycle of coding was completed, the codes were grouped together into categories based on the similarities and common themes between them. Themes are discussed in detail in Chapter 4: Results.

Figure 11: Second cycle codes with hierarchies

Grouped codes:



Ungrouped Codes



3.5.2. Quantitative Data Analysis

Having discussed the analysis of interview data, attention shifts to the quantitative analysis, using structural equation modelling. The first step is to specify the model (Kline, 2015). For the present study, this is done with reference to the research questions and hypotheses to be tested.

3.5.2.1. Structural Models and Hypotheses

The first set of hypotheses relate to the relationship between corporate reports and the information environment in the equity capital market.

The structural models were linked to the research questions for this study.

RQ1 is: What is the effect of the quality of integrated report information on the market?

To investigate further, separate hypotheses were created for analysts, who are regarded as sophisticated users of financial information and for the information environment of the market as a whole.

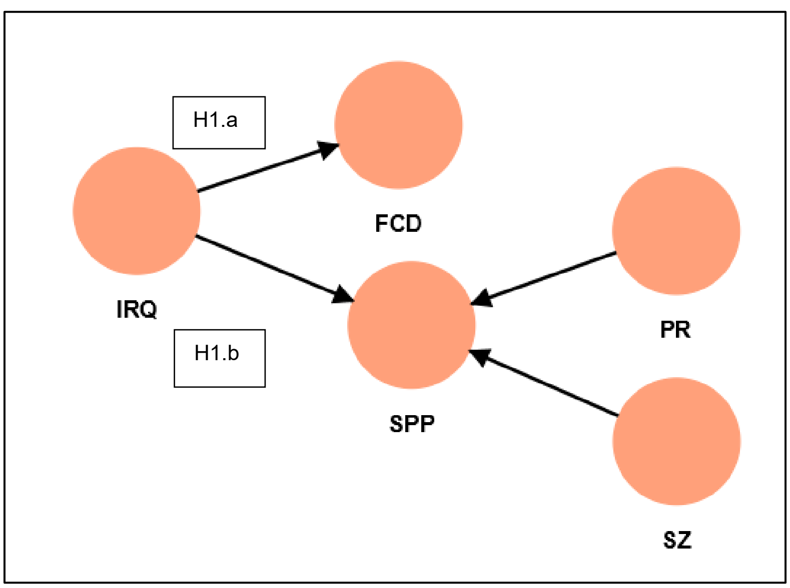
H1: The quality of equity analysts' forecasts improves with an increase in the quality of information in the integrated reports.

H1.a. The quality of information contained in a company's integrated reports has a positive relationship with the quality of analysts' forecasts for that company.

To examine the effect of integrated report quality on the information environment as a whole, we include the following sub-hypothesis:

H1.b. The quality of information in a company's integrated reports has a positive relationship with share price performance of that company.

Figure 12: Structural Model 1 (SM1)



Where: IRQ = Integrated Report Quality; FCD = Forecast Decision; SPP = Share Price Performance; SZ = Size; PR = Profitability. Source: Researcher's Own (created in SmartPLS)

These hypotheses were tested using the initial structural model, SM1. In this path diagram, integrated report quality (IRQ) and forecast decision (FCD) are latent variables while share price performance (SPP) and related control variables are observed variables.

Profitability and Size have been included in the structural model but not linked to any hypotheses. The effect of these control variables on share price performance is widely accepted (Ohlson, 1995; Kothari, 2001; Baker *et al.*, 2022).

The second stage of the study focuses on the way in which the information is used in the forecasting process. It's aim is to evaluate the influence of behavioural bias on the decision processes of investors.

RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias?

H2: Poor quality integrated reports increase analysts' proclivity to behavioural bias

For H2, we test the relationship between the quality of integrated reports and *each* bias.

RQ3: What is the effect of behavioural biases on analysts' forecast decisions?

H3. The bias of equity analysts has an effect on the quality of their forecast decisions

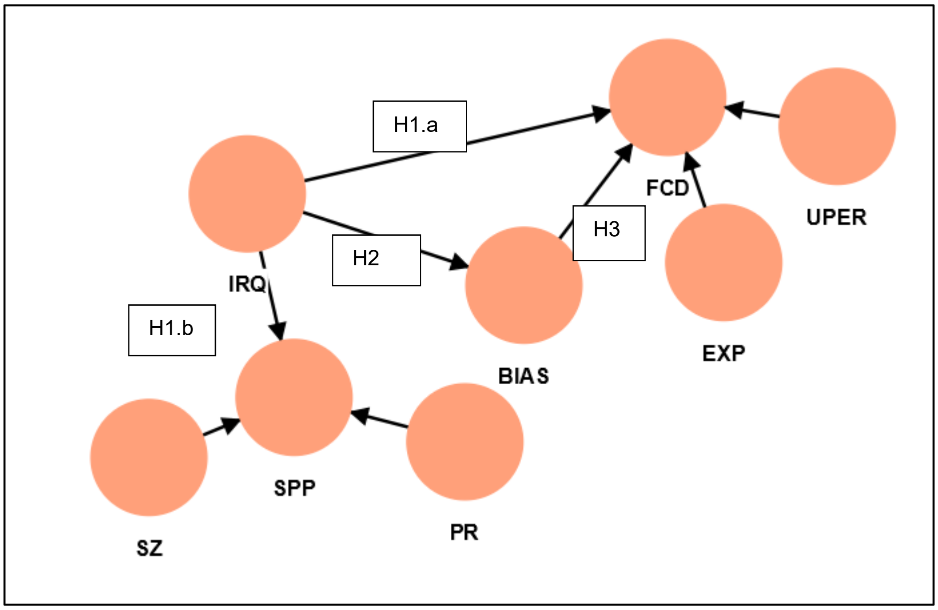
For H3, we test the relationship between *each* bias and the quality of analysts' forecasts.

In order to test these hypotheses, both qualitative and quantitative data were used. Specifically, an extension of Model 1 was used.

The extension incorporates the hypothesised effect of various behavioural biases discussed in Section 2.11: Cognitive and emotional biases. Each bias is a latent variable, measured by observable indicator variables[10]. As with share price performance, a control variable is included for Forecast Decision. This variable is named "Upward Error" and captures the difference between the target and actual price forecasts when the target price estimate was higher than the actual price achieved. This variable is included based on the large body of research that has found that analysts are incentivized to produce positive recommendations to incentive trading activities via their employers, as discussed in Section 2.12.1. Other variables are as per SM1.

[10] Indicator variables are detailed in Figure 14: Measurement Model and in Section 3.5.2. on the Measurement of variables

Figure 13: Structural Model 2 (SM2)



Where: BIAS = Behavioural biases; IRQ = Integrated Report Quality; FCD = Forecast Decision; SPP = Share Price Performance; SZ = Size; PR = Profitability; UPER = Upward Error

Source: Researcher's Own (created in SmartPLS)

SM2 in Figure 13 can also be expressed as:

$$\eta = \Gamma\Xi + \varsigma \qquad \textit{Equation 1}$$

where η is the dependent variable; Ξ is a vector of independent latent variables; Γ is a vector is regression coefficients; and ς is the residual for the structural equation.

For this study, the following structural models are estimated to evaluate the effect of integrated report quality and each bias on forecast decision quality.

$$FCD_{it} = \gamma_1 IRQ_{it} + \gamma_2 AVL_{it} + \gamma_3 LAV_{it} + \gamma_4 HRD_{it} + \gamma_5 OVC_{it} + y_6 UPERR_{it} + \gamma_7 EXP_{it} + \varsigma \qquad \textit{Equation 2}$$

$$SPP_{it} = \gamma_1 IRQ_{it} + \gamma_2 PR_{it} + \gamma_3 SZ_{it} + \varsigma \qquad \textit{Equation 3}$$

where: FCD is forecast decision; SPP is share price performance; IRQ is integrated report quality; AVL is the availability bias; LAV is the loss aversion bias; HRD is the herding bias; OVC is the overconfidence bias; UPERR is the upward error; EXP is the number of years of experience; PR is profitability; SZ is size and ς is the residual for the structural equation. Profitability is approximated as return on assets and size is approximated by the natural logarithm of total assets, as per Barth et al. (2017).

The assumptions of SEM are similar to those of ordinary least squares regressions. These assumptions are: multivariate normality, no systematic missing data, a sufficiently large sample and no multicollinearity in the structural model (Bollen & Noble, 2011)[11]. In some cases, variables are expected to have non-normal distributions (e.g. personality characteristics). In these cases, it does not make sense to apply a normalising transformation, despite the available option to do so (Kline, 2015). For such data, inferences may be more meaningful if researchers use an estimation method that does not assume normality, such as partial least squares (PLS).

Partial least squares structural equation modelling (PLS-SEM) is increasing in popularity relative to the dominant covariance-based structural equation modelling (CB-SEM). This increase in popularity can be attributed to the ability of PLS-SEM methods to estimate complex models, with many latent and non-latent constructs, without imposing distributional requirements on the data (Hair, Risher, Sarstedt & Ringle, 2019). PLS-SEM constructs partial model structures by combining principal component analysis with ordinary least squares regressions (Hair *et al.*, 2018). CB-SEM uses the covariance matrix of the sample and estimates model parameters considering only common variance. However, PLS-SEM uses the total variance to estimate parameters. The path coefficients in PLS-SEM are similar to beta weights in a regression analysis. In addition, R-squared values can be produced for the dependent constructs in the study. The algorithm calculates partial regression relationships in the measurement and structural models by using several, separate, ordinary least squares regressions.

According to Hair *et al.* (2019), PLS-SEM should be used when (amongst others):

- the data consist of financial ratios or similar artifacts[12];
- the sample size is restricted and
- the data is not normally distributed.

A key advantage of PLS SEM over the covariance-based SEM is the minimal requirements for specific measurement scales and large sample sizes (Hair *et al.*, 2019). The former involves "bootstrapping", an approach whereby a large number of sub-samples are drawn from the original sample (Hair *et al.*, 2019). Therefore, besides PLS not making any distributional assumptions, PLS can accommodate smaller sample sizes than other SEM approaches. Based on the results of the tests for multi-variate normality in this research (critical ratio of 106.940), as well as the relatively small sample size, the PLS approach was favoured. The SmartPLS4 statistical package (Hair *et al.* 2019) was used to evaluate the measurement model and test the hypotheses in the structural model. SmartPLS is a software programme with a graphical interface that is commonly used for PLS-SEM (Hair *et al.*, 2019; Kline, 2015).

3.5.2.2. Measurement of variables

In addition to the measurement approximations required to quantify variables of interest in a regression, the structural equation model analysis involves latent constructs which are not directly observable (Kline, 2015). Ittner *et al.* (1997) used latent variables in a partial least squares structural equation model to evaluate the choice of financial and non-financial measures in executive's remuneration contracts. The authors support their use of latent variable regression techniques by explaining that these techniques are designed to

[11] Further results of validity and reliability for the models are contained in Section 4.3.2. of the Results section.

[12] Such as firm-fixed factors (Richter *et al.*, 2016)

accommodate underlying theoretical constructs (or latent variables) that are imperfectly measured by their observable indicators.

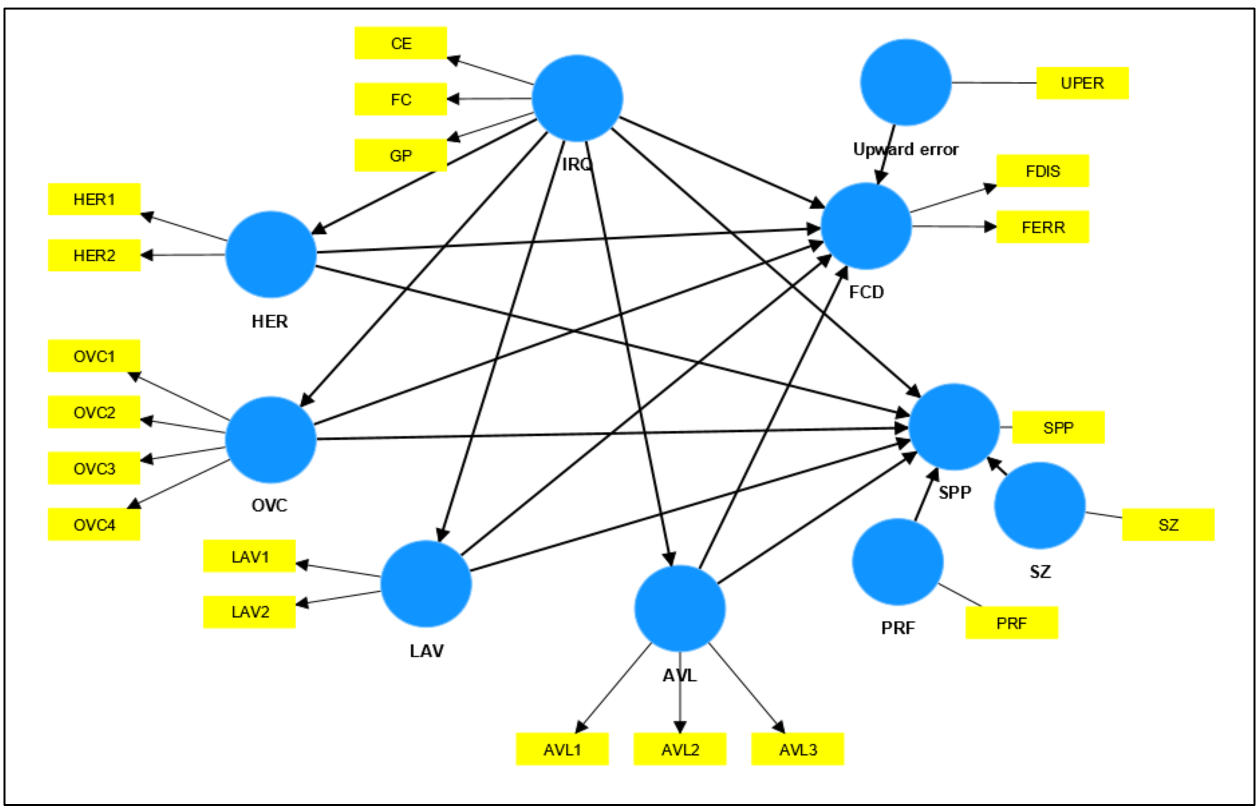
In this study, the latent constructs are quality of integrated reports, quality of forecast decisions and each bias. The nature of these variables further validates the use of PLS-SEM instead of covariance-based SEM. For example, Ittner *et al.* (1997) created the latent variable of "strategy" with four indicators: research and development expenditure relative to sales, the market-to-book ratio, the number of employees scaled by sales and the number of new products introduced. Although the present research does not comprise formative constructs, we use ratios in a similar manner to create constructs. The measurement of the constructs can be expressed as:

$$x_{ij} = \lambda_{ij}\xi_i + \delta_{ij} \qquad \textit{Equation 4}$$

where x_{ij} is the j^{th} indicator of the latent variable ξ_i; λ_{ij} is the loading of the indicator (x_{ij}) to the latent variable (ξ_i); and δ_{ij} is the measurement error.

The latent variables and indicators used in this study are shown in a measurement model in Figure 2. Measurement approximations were used for each indicator variable as well as the observable (or non-latent) variables of Size, Profitability and Share Price Performance.

Figure 14: Measurement model



Where: IRQ: Integrated Report Quality; FCD: Forecast Decision; SPP: Share Price Performance;

OVC: Overconfidence; LAV: Loss Aversion; HER: Herd behaviour; AVL: Availability

Source: Researcher's Own (created in SmartPLS)

The rest of this section contains a detailed discussion of the measurement approximations for firstly, the latent variables and secondly, the observable variables.

3.5.2.3. Latent variable measurement approximations

As detailed in the section of SEM in Accounting and Finance Research in Chapter 2, finance and accounting research, typically uses survey questionnaires to gather data for indicator variables. The questionnaires can be based on existing scales from prior research (as in Schmidt, Riley and Church, 2020) or the questions can be developed from scratch, based on the findings of prior research (as in Newman *et al.*, 2013). Their research used PLS- SEM to evaluate buy-side analysts' use of accounting and other information. In creating their unique questionnaire, the researchers ensured that they complied with several important measurement criteria.

These criteria are discussed in Schumacker and Lomax (2004). Indicator variables should have data on a ratio or interval scale. It is also advisable that the indicators have equidistant data points or a consistent scale. The latter criterion is relevant for data that uses Likert-scale survey data. Importantly, the combining of binary and categorical data with metric indicators in a latent variable's measurement model can lead to the misinterpretation of results. These considerations were applied in the formulation of the indicators for the latent variables in the present study. The use of financial information instead of survey data as indicators, has as precedent, the research by Titman and Wessels (1988) and Ittner *et al.* (1997).

Another consideration in the formulation of latent constructs is whether they are reflective or formative. For reflective constructs, observed variables or measurement indicators are reflective of the underlying construct. Formative constructs define or form the construct itself (Kline, 2015, Hanafiah, 2020). In Bruckmaier *et al.* (2021), the authors evaluate whether the seminal heuristics in Kahneman and Tversky (1986) form a reflective or formative construct. They consider the extent of the intercorrelations between individual indicators of each construct, and if the observed variables can manifest simultaneously. They conclude that the constructs should be reflective. Kline (2015) explains reflective and formative constructs in terms of direction of causality. For a reflective construct, the latent variables are assumed to cause the observed variables. For formative constructs, the indicators are specified as causes of the latent variables. Hanafiah (2020) explains another important distinction between reflective and formative constructs. In a formative model, all measurement items do not necessarily need to have a high correlation, whilst in the reflective model, there is a need for the measurement items to have a high correlation. Three criteria are suggested for the determination of whether a construct is formative or reflective. They are detailed below and applied to the present study.

1. The nature of the construct. If a latent construct is present independently of its measures, this is indicative of a reflective construct. For this study, the latent variables of integrated report quality, biases and forecast decision quality exist independently of each of the measures. For example, a bias such as overconfidence can exist even without the indicator of frequent trading.
2. The direction of causality. The assumption of reflective models is that causality flows from the construct to the indicators. This means that a change in the construct will correspondingly affect the indicators. Conversely, formative models suggest that

causality flows from the indicators to the construct, meaning that a change in the indicators leads to a change in the studied construct. Extending the study's example of overconfidence, it is not the indicator (frequency of trading) that causes overconfidence, but rather overconfidence that manifests as frequent trading.

3. Characteristics of the indicators. In the case of formative constructs, the nature of the indicators as well as the number of indicators affects the theoretical meaning of the construct. The meaning of the construct can change if there is an addition or removal of an indicator. This is not the case for reflective constructs, which can have any number of indicators, provided the factor loadings meet certain criteria (Bollen & Noble, 2011).

Therefore, in the present study, reflective constructs were deemed most appropriate for each variable that they represented.

According to Bollen and Noble (2011) indicators in the measurement model should only be assessed if the factor loadings are greater than 0.6. In addition, each latent variable should have a minimum of two indicators and the Cronbach alpha for each variable should not be below 0.6.

These guidelines were followed in the formulation of the indicators in the measurement model. In addition, the measurement indicators were developed, based on prior literature. The rest of this section contains a discussion of the measurement approximations used in relevant prior literature and develops measurement proxies for the indicators of each latent variable.

3.5.2.4. Loss Aversion

The empirical studies on loss aversion are dominated by experimental research. Typically, participants are presented with scenarios in which they are required to compare possible gains and losses and make a hypothetical decision. For example, Gächter, Johnson and Hermann (2022) presented a lottery choice task to 660 randomly selected consumers of a car manufacturer. Participants were presented with several possible scenarios and asked to make a decision. An example of a typical question in experimental research on loss aversion, is presented in Figure 15.

Figure 15: Example of a question in an experimental design study

In the following table you find a list of coin tosses with different payoffs. **The payoffs differ in how much you lose if the coin turns up heads.** For each row you need to indicate whether you want to toss the coin or not. To determine your payoff, one of the six rows will be randomly selected by rolling a six-sided die. If you have indicated that for the randomly selected row you want to toss the coin, then the coin will be tossed, and you will be paid accordingly.

	I don't want to toss the coin	I want to toss the coin
1. If the coin turns up heads, then you **lose €2**; if the coin turns up tails, you **win €6**.	O	O
2. If the coin turns up heads, then you **lose €3**; if the coin turns up tails, you **win €6**.	O	O
3. If the coin turns up heads, then you **lose €4**; if the coin turns up tails, you **win €6**.	O	O
4. If the coin turns up heads, then you **lose €5**; if the coin turns up tails, you **win €6**.	O	O
5. If the coin turns up heads, then you **lose €6**; if the coin turns up tails, you **win €6**.	O	O
6. If the coin turns up heads, then you **lose €7**; if the coin turns up tails, you **win €6**.	O	O

Fig. 1 The lottery choice task

Source: Gächter *et al*. (2022)

Arkes and Blumer (1985) also used both hypothetical and real-life scenarios in a study to evaluate the impact of the “sunk cost effect’ (p. 124). Questionnaires were administered to determine the extent to which costs that had already been incurred impacted decisions about future actions. Their analysis on data from real life scenarios included a comparison of the upfront price paid for a series of theatre shows and the number of theatre shows actually watched. The authors found an association between the price paid for the subscription and the number (and timing) of shows watched. Hypothetical scenarios were described to participants in a questionnaire. Scenarios involved a project investment decision with sunk costs and various possible returns. The results showed that when sunk costs were greater, participants inflated their estimates of the likelihood of success of the project. The researchers concluded that there is a greater tendency to continue with a course of action once an investment in money, effort or time is made.

In non-experimental research, Odean (1998a) and Barber and Odean (1999) tested whether investors sell their winners too soon and hold on to losers for too long. Their research provided an empirical application of prospect theory and the disposition effect – due to the desire to avoid regret, investors tend to hold their losing investments too long and sell their winners too soon (Kahneman & Tversky, 1979; Shefrin & Statman, 1985). In developing measurement approximations, Odean (1998a) explains that it would be insufficient to look at the number of shares sold for gains and compare that to the number of shares sold at a loss. This is because, in an upward-moving market, it would be expected that more of the shares sold would be winners, even if the investors were indifferent to selling winners or losers. Therefore, the measurement approximations used in their study considered the frequency with which investors sell winners and losers relative to their opportunities to sell each. The following measurement approximations for the proportion of gains realised (PGR) and the proportion of losses realised (PLR) were used.

$$PGR = \frac{Realised\ gains}{Realised\ gains + Paper\ gains} \qquad \textit{Equation 5}$$

$$PLR = \frac{Realised\ losses}{Realised\ gains + Paper\ losses} \qquad \textit{Equation 6}$$

For these calculations, paper gains or losses are defined as unrealised gains or losses (on shares that were not sold), being movements from the initial price of the share to the current day. A large difference in the proportion of losses realised would indicate that investors are more willing to realise gains or losses. In this manner, the authors quantified the investor reluctance to sell losers and preference for selling winners. Similarly, Asquith *et al.* (2005) found that the increase in stock price before it was recommended as a “buy” would be less than the decrease in stock price before a “sell” was recommended. These findings provide further evidence of analysts’ reluctance to issue “sell” recommendations rather than “buy” recommendations. Continuing this line of reasoning, loss averse analysts would be less likely to issue “hold” recommendations and would instead issue the more optimistic “buy” recommendation. Similarly, loss averse analysts would be less likely to issue “sell” recommendations and would instead issue the more optimistic “hold” recommendation.

Therefore, the indicators for loss aversion are calculated for each firm, *i* at time *t* as the total number of "buy" recommendations issued by the analysts following the firm, scaled by the total number of "hold" recommendations issued for the company,

$$LAV1_{i,t} = \frac{Total\ number\ of\ \text{"buy"}\ recommendations_{i,t}}{Total\ number\ of\ \text{"hold"}\ recommendations_{i,t}} \qquad \textit{Equation 7}$$

and LAV2 is calculated as the total number of "hold" recommendations issued by the analysts following the firm, scaled by the total number of "sell" recommendations issued for the firm.

$$LAV2_{i,t} = \frac{Total\ number\ of\ \text{"hold"}\ recommendations_{i,t}}{Total\ number\ of\ \text{"sell"}\ recommendations_{i,t}} \qquad \textit{Equation 8}$$

For LAV1, if there were no "hold" recommendations and there were only "buy" recommendations, LAV takes the value of one. Similarly, for LAV2, if there were no "sell" recommendations and there were only "hold" recommendations, a value of 1 was assigned to the indicator.

3.5.2.5. Overconfidence

When analysts overestimate their forecasting abilities, they effectively overestimate their ability to generate insights or identify signals that they believe other analysts may ignore (Daniel, Hirshleifer & Subrahmanyam, 1998; Hilary & Menzly, 2006). More overconfident analysts are likely to diverge from consensus estimates as they overestimate their ability to identify arbitrage opportunities that other analysts may not have detected. The measurement approximation for the first indicator of overconfidence (OVC1) in this study, is therefore derived from the phenomenon of self-serving attribution, detailed in Section 2.11.2. of this study. It follows Hilary and Menzly (2006), who created the variable "DEV", being the absolute value of the difference between the analysts' forecasts and the consensus forecast, where consensus forecast is the average forecast for each firm in the forecast period.

For this study, we measure the first indicator of overconfidence (OVC1), for firm *i* at time *t*, as the average percentage diversion of each analyst from the consensus estimate for the forecasted period.

$$OVC1_{i,t} = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{Estimate_{i,t+1} - Consensus_{i,t+1}}{Consensus_{i,t+1}}\right) \qquad \textit{Equation 9}$$

Where n is the number of forecasts for firm *i* at time *t* and *j* represents each analyst.

Similarly, OVC2 was calculated for each firm, *i* at time *t*, as the number of recommendations that differ from the consensus, scaled by the total number of recommendations for that firm.

$$OVC2_{i,t} = \frac{Number\ of\ recommendations\ differing\ from\ consensus_{i,t}}{Total\ number\ of\ recommendations_{i,t}}$$

Equation 10

Recommendations were coded as either buy, hold or sell, per the table of Recommendation Coding in Appendix N. These codes are as per the Bloomberg Analyst Recommendations Index Methodology (Bloomberg, 2023).

As detailed in Section 2.11.2. of this study, higher levels of overconfidence have been shown to be associated with more frequent trading (Barber & Odean, 1999; Odean, 1998b), because overconfident investors feel they have identified arbitrage opportunities where other investors have not. We extend this notion to the frequency of issuing recommendations to develop the third measurement approximation for overconfidence (OVC3). OVC3 is measured for firm *i*, at time *t*, as the average of the number of recommendations issues for the firm in the period, scaled by the total number of recommendations issued by analysts following firm *i,* for all other firms that they cover in the period of analysis.

$$OVC3_{i,t} = \frac{1}{n}\sum_{j=1}^{n} \frac{Number\ of\ recommendations\ for\ firm\ i\ by\ analyst\ j\ at\ time\ t}{Total\ number\ of\ recommendations\ issued\ by\ analyst\ j\ at\ time\ t}$$

Equation 11

More overconfident analysts have also been shown to be more confident about information that they have generated themselves, instead of public signals. Therefore Daniel *et al.* (1998) define overconfident investors as those who overestimate the accuracy of their own private information over the information that has been communicated to the public. Similarly, Hilary and Menzly (2006) cite overconfidence as the reason for analysts weighting their own private information over publicly available information. The present study has a specific focus on integrated reports issued by the company. It seems logical then, that the proxy for "publicly available information" should be the integrated reports. However, given the indications from the descriptive statistics (Section 4.3.1.) and the interview results (Section 4.2.), we use the annual financial results as the publicly available information source. The measurement approximation for OVC4 is premised on the notion that overconfident analysts will underweight public information relative to their own private information about the company. OVC4 is therefore measured as the number of days after the date of release of the annual results that the analysts take to release their recommendation relating to the firm, scaled by the average number of days that the analysts take to issue recommendations for the other firms that they follow. In other words, this measurement approximation shows the relative timing of the analysts' recommendations for firm i compared to the average timing of recommendations for other firms covered in the period.

$$OVC4_{i,t} = \frac{1}{n}\sum_{j=1}^{n} \frac{Recommendation\ issue\ date_{i,t,j} - Annual\ results\ release\ date_{i,t}}{Average\ number\ of\ days\ that\ the\ analysts\ take\ to\ issue\ their\ recommentaions\ for\ all\ firms_{t}}$$

Equation 12

The researcher used the JSE SENS information for the dates on which the integrated results were released. If no information was discernible from the JSE SENS, relevant dates were obtained from the "Investor Relations" portal on the companies' websites.

3.5.2.6. Availability

As discussed in the literature review in Section 2.11.4., the availability heuristic has been found to influence the decisions of analysts and investors. For example, Barber and Odean (2008) found that investors tend to prefer shares that have recently caught their attention by being featured in the news or experiencing high normal trading volume. Crawford, Roulstone and So (2014) focused on the formulation of analyst recommendations for a firm, when coverage was initiated. They found that the recommendations provided by the analysts depended largely on the information that was provided by other analysts who cover the firm. For the purposes of this study, we measure the first indicator of availability (AVL1) as the number of analysts following the firm *i* at time *t*, scaled by the total number of analysts issuing recommendations over the period.

$$AVL1_{i,t} = \frac{Number\ of\ analysts\ following\ firm\ i\ at\ time\ t}{Total\ number\ of\ analysts\ issuing\ recommendations\ over\ the\ period\ t}$$

Equation 13

Lee *et al.* (2008) also examined the effect of the availability heuristic on analysts' forecasts. They posit that a rational analyst's forecast would incorporate all factors driving the potential performance of a company. However, due to the influence of the availability heuristic, forecasts would be overinfluenced by the current state. Therefore, an implication of the availability heuristic is that analysts will rely heavily on most recent growth to predict the future. Such behaviour is rational if growth rates are shown to persist over time. However, the JSE has been shown to exhibit significant volatility (Rupande, Muguto & Muzindutshi, 2019). In the present study, we develop indicators that show the emphasis placed by the analyst on more recent company profitability relative to less recent company profitability. AVL2 and AVL3 are measured as the difference between the association of current share price forecasts with most recent company performance and the association of current share price forecasts with less recent company performance.

First, we estimate the association of the most recent forecast for firm *i* at time *t* with the most recent company performance (MR2) as:

$$MR2_{i,t} = \left(\frac{Forecasted\ share\ price_{i,t+1} - Actual\ share\ price\ _{i,t}}{Actual\ share\ price_{i,t}}\right) - \ \Delta(Company\ ROA_{i,t,t-1})$$

Equation 14

Then, we estimate an association of the most recent forecast for firm *i* at time *t* with the less recent company performance (LR2) as:

$$LR2_{i,t} = \left(\frac{Forecasted\ share\ price_{i,t+1} - Actual\ share\ price\ _{i,t}}{Actual\ share\ price_{i,t}}\right) - \ \Delta(Company\ ROA_{i,t,t-3})$$

Equation 15

Finally, the measurement indicator of AVL2 for firm *i* at time *t* is computed as the average of the difference between LR2 and MR2 for all analysts following the firm.

$$AVL2_{i,t} = LR2_{i,t} - MR2_{i,t}$$ *Equation 16*

Similarly, we estimate AVL3 using the same formulae except for one period prior, since we have time series data for six years.

$$MR3_{i,t} = \left(\frac{Forecasted\ share\ price_{i,t+1} - Actual\ share\ price\ _{i,t}}{Actual\ share\ price_{i,t}}\right) - \Delta(Company\ ROA_{i,t,t-1})$$

Equation 17

$$LR3_{i,t} = \left(\frac{Forecasted\ share\ price_{i,t+1} - Actual\ share\ price\ _{i,t}}{Actual\ share\ price_{i,t}}\right) - \Delta(Company\ ROA_{i,t,t-4})$$

Equation 18

$$AVL3_{i,t} = LR3_{i,t} - MR3_{i,t}$$ *Equation 19*

3.5.2.7. Herd behaviour

Research on herd behaviour amongst analysts commonly measures their propensity to follow a target such as the "herd's" consensus (Welch, 2000 p.374) or broker consensus. The broker consensus can then be defined in terms of the target price or the target recommendation, such as buy or sell. Several studies (Gleason & Lee, 2003; Clement & Tse, 2005; Song, Kim & Won, 2009) classify a forecast as "bold" , as opposed to a herding forecast, if it deviates from the consensus forecast or even the analyst's own prior forecast.

Therefore, we measure herding using the difference between each analyst's current share price forecast and the average of the analysts' previous share price forecast for that company. In this manner, we attempt to capture the propensity for analysts to herd around their own prior forecasts. We use the inverse because, according to the principles of structural equation modelling, a large value of the indicator must correspond to a larger level of the latent variable (herding)/ For the purposes of this study, we do not measure the difference between each analyst forecast and the consensus forecast because the variance in analysts' forecasts is used as an indicator for the latent variable of forecast decision quality (as detailed in the following section in this chapter).

$$HER1_{i,t} = \frac{1}{n}\sum \frac{|\ Current\ Share\ Price\ Forecast_{i,j,t} - Previous\ Share\ Price\ Forecast_{i,j,t-1}|}{Average\ of\ Previous\ Share\ Price\ Forecast_{i,j,t-1}}_{i,j,t}$$

Equation 20

Welch (2000) highlights a limitation of discrete measurements of herding. When analysts herd, they herd around a prevailing target – i.e. a forecast that was issued prior to their own. It is contended that measurement approximations should reflect the sequence of decisions using informational cascades (Bikhchandani & Sharma, 2000; Welch, 2000). In fact, the seminal work on herding by Banerjee (1992) is based on a model of sequential decision making, where each decision maker considers previous decision makers before making their own choices. We incorporate the sequence of forecasts in the second indicator of herding, for each firm as the average of the number of days between each analyst's forecast and the date of the first forecast for that firm in that period (HER2). We scale this by the difference between the last and first forecast for the firm, to account for the fact that some firms may take longer (on average) to analyse than others. Again, the inverse is used so that a larger level of the indicator shows a larger value of the latent variable.

$$HER2_{i,t} = \frac{1}{n}\sum \frac{Date\ of\ the\ analyst\ forecast_{i,t} - Date\ of\ the\ first\ forecast_{i,t}}{Date\ of\ the\ last\ forecast_{i,t} - Date\ of\ the\ first\ forecast\ _{i,t}} \qquad \textit{Equation 21}$$

3.5.2.8. Forecast decision quality

Hong and Kubik (2003) create a measure of the absolute forecast accuracy of an analyst. For firm *j* in year *t*, the accuracy of the analyst's earnings forecast is provided as the absolute difference between their forecast and the actual earnings of the firm, $A_{j,t}$, scaled by the stock price, P_j. (to incorporate the size of the firm and its earnings). However, since analysts cover more than one firm in a year, the study incorporates an aggregate measure of forecast accuracy being the average forecast errors of an analyst for the year. Since the measure is of analyst accuracy and not analyst error, an inverse is used:

$$Absolute\ Forecast\ Accuracy_{i,t} = \frac{1}{n}\sum Forecast\ Error_{i,j,t} \qquad \textit{Equation 22}$$

Imam and Spence (2020) compute metrics that reflect each aspect of analyst forecast accuracy – directional accuracy as well as point accuracy. Point accuracy measures the difference between the target and actual price, with values closer to zero representing higher accuracy. Therefore, point accuracy is measured as:

$$Point\ accuarcy = \frac{P_{tgt} - P_t}{P_{12}} \qquad \textit{Equation 23}$$

Where P_{tgt} is the target price of the share and P_{12} is the actual price at the end of the 12-month horizon. Since the measure of Ahmed and Flint (2020) does not incorporate absolute values, a positive value indicates a more optimistic forecast whilst a negative value indicates a more pessimistic view of the share price performance. The present study requires an average across analysts for each company. If we were to follow this measurement as a precedent, we would show a high forecast accuracy if we add optimistic and pessimistic forecasts for the same company.

Therefore, for thus study, we compute the absolute forecast accuracy. According to the principles of SEM, an increase in the indicator variable must be interpreted as an increase in its latent construct of forecast quality. Therefore, we also use the difference of forecasted price and actual price. However, we deviate from Hong and Kubik (2003) and align with Barth *et al.* (2017) as we aggregate forecast accuracy for all the analysts following a company. This deviation is necessary since the integrated report quality scores are provided by company. For each firm, forecast error in relation to company *i*, at time *t* is calculated as the inverse of the average of the absolute difference of forecasted share price and actual share price, 12 months from the date of forecast (or soonest working day), scaled by the actual stock price at forecast date, for all analysts *(j)* following the firm. In summary, we measure forecast accuracy or FERR as:

$$FERR_{i,t} = \frac{1}{n}\sum_{j=1}^{n}\frac{|Forecasted\ share\ price - Actual\ share\ price\ in\ 12\ months|}{Actual\ share\ price\ in\ 12\ months}i,j,t$$

Equation 24

As in Chen, Xie and Zhang (2017), we measure quality of analysts' forecasts by the accuracy as well as the dispersion of forecasts amongst analysts. We rationalise that greater forecast dispersion indicates less agreement amongst analysts, possibly due to less reliance on corporate reports or due to analyst bias. If information in corporate reports is unambiguous, there should be low variation in analysts' forecasts. This assertion is also expressed in a study that examines information uncertainty in the context of asset securitisation (Cheng, Dhaliwal & Neamtiu, 2011). To represent information uncertainty or "firm level information asymmetry" (p.549), analyst forecast dispersion was used.

We follow the precedent of several prior studies such as Chen *et al.* (2014) and Zhou *et al.* (2017) as we measure analyst forecast dispersion as the standard deviation of analysts' forecasts. As with FERR in Equation 24, we use the negative of the standard deviation so that an increase in the indicator variable implies an increase in its latent construct. We measure forecast dispersion as the inverse of the standard deviation of forecasts issued by all analysts following the firm, *i* at time *t* (Chen, Xie & Zhang, 2017).

$$FDIS_{i,t} = \frac{1}{\sigma}$$

Equation 25

3.5.2.9. Integrated report quality

As discussed in Section 2.4, for the purposes of this study, the quality of integrated reports is represented by the average of the detailed scores of the adjudicators in the EY Integrated Reporting awards. The report quality scores were assigned per report, per aspect of quality, by each of three experts, independently. These quality scores were used in Barth *et al.* (2017). The authors examined the scoring sheets and evaluation criteria and were satisfied that they were consistent with the IIRC framework, and therefore a reliable measure of integrated report quality (IRQ). The scoring was done according to each of the three categories of Guiding Principles (GP), Content Elements (CE) and Fundamental Concepts (FC) (See Appendix A for detail of each category).

Since Barth *et al.* (2017) used a regression, with IRQ as a test variable, their measure of each firm's IRQ was based on a single score, combining all three categories. The present study uses a structural equation model, and therefore treats IRQ as a latent construct. Therefore, we are able to represent each aspect of quality separately, as several indicators of a single latent construct. The measurement of each indicator of IRQ (CE, FC and GP) is calculated as the average of the percentage scores given by the award adjudicators for each firm *i* for each period, t_{-1}. We use t_{-1} as the score relating to the report of one period prior to the time at which the forecast is issued (t_0). As detailed in Section 3.4., the scores of each of the three expert adjudicators (*j*) of the EY Excellence in Integrated Reporting Awards are included in the calculation of the IRQ indicator variables in Equations 26, 27 and 28.

$$CE_{i,t-1} = \frac{1}{3}\sum_{j=1}^{3} CE_{i,t-1,j}$$ *Equation 26*

$$FC_{i,t-1} = \frac{1}{3}\sum_{j=1}^{3} FC_{i,t-1,j}$$ *Equation 27*

$$GP_{i,t-1} = \frac{1}{3}\sum_{j=1}^{3} GP_{i,t-1,j}$$ *Equation 28*

3.5.2.10. Non-latent variable measurement approximations

Several non-latent or observable variables were used in the model. These variables are not represented using indicator variables. Instead, they are represented using measurement approximations which are commonly used in prior studies. The measurement approximations of non-latent variables are detailed in the rest of this section.

Share price performance (SPP)

$$SPP_{i,t_0} = \frac{Share\ price_{i,t_0} - Share\ price_{i,t_{-1}}}{Share\ price_{i,t_{-1}}}$$ *Equation 29*

where t_{-1} is the period covered by the integrated report.

Profitability (PR) or Return on Assets:

$$PR_{i,t-1} = \frac{Income\ before\ extraordinary\ items\ as\ reported\ at\ the\ end\ of\ the\ period_{i,t-1}}{Total\ assets\ at\ the\ start\ of\ the\ year_{i,t-1}}$$

Equation 30

where t_{-1} is the period covered by the integrated report.

$$SZ_{i,t-1} = \ln\left(Total\ assets\ at\ the\ start\ of\ the\ year_{i,t-1}\right)$$ *Equation 31*

where SZ is company size and t_{-1} is the period covered by the integrated report.

3.5.2.10.1. Upward error

As discussed in Section 2.12.1., Ahmed and Flint (2020) disaggregated forecast accuracy into point accuracy and directional accuracy. Directional accuracy is particularly relevant for the measurement of "upward error" in the present study. Ahmed and Flint (2020) create a "confusion matrix" and classify forecast errors as either Type 1, where the forecasted share price movement was upward whilst the actual share price movement was downward, or Type 2, where the forecasted movement was downward whilst the actual share price movement was upward. Subsequently, positive precision was measured as the ratio of true upward predictions to total upward predictions.

In the present study, the variable of "upward error" was created as a control variable, to assess the potential effect of analysts' being overly optimistic in their predictions relating to each firm. This unjustifiable optimism can result from incentive conflicts as detailed in Mokoaleli- Mokateli *et al.* (2009). In their seminal study on incentive conflicts, Hong and Kubic (2003) created a relative forecast optimism score. The score was computed by first creating a dummy variable that takes a value of one if the analyst's forecasts is greater than the consensus forecast for that period. This value is then averaged over three years to find a relative forecast optimism score per analyst.

Similarly, we calculate an optimism score or "upward error" for each company year. We measure "upward error" for firm *i* at time *t*, as the number of incorrect forecasts that exceeded the consensus forecast scaled by the total number of incorrect forecasts for that company in that period:

$$Upward\ Error_{i,t} = \frac{Number\ of\ incorrect\ forecasts\ exceeding\ the\ consensus\ forecast_{\ i,t}}{Total\ nunber\ of\ incorrect\ forecasts_{\ i,t}}$$

Equation 32

3.5.2.10.2. Analysts' experience

As detailed in Section 3.5.2. on Analyst Experience, there is a large body of literature which explores the potential effects of analysts' personal characteristics on their forecast accuracy, investor reaction to their predictions and the analysts' career progression. LinkedIn.com (a large professional networking website) has been used to collect data on analysts' background and experience for these studies. For example, Fang and Hope (2021) used LinkedIn as a source of background information about the analysts, including the number of years in the sell-side research industry. Bradley, Gokkaya, Liu and Xie (2017) hand-collected data on analysts' employment history from LinkedIn.

Therefore, for the purposes of the present study, analyst experience was defined as the number of years in the sell-side research industry, as evidenced from the analysts' employment history from LinkedIn. Since the analysis in this study has the firm as the unit of analysis, we compute, for each firm *i*, the average number of years of experience of the analysts (*n*) following the firm at time *t*.

$$EXP_{i,t} = \frac{1}{n}\sum_{j=1}^{n} Experience_{\ i,j,t}$$

Equation 33

Where the analyst experience could not be obtained from LinkedIn either because their profile could not be found or had not been updated, the average number of years of experience of the analysts who issued recommendations in that period for the firm, was used. This approach was followed for six analysts, and the recommendations that were issued attributed to team coverage.

3.6. Validity and Reliability

Threats to validity and/ or reliability can occur at any stage during the research process (Johnson & Onwuegbuzie, 2004). These threats, along with the researchers' responses in this study, are presented collectively in the remaining sections of this chapter. As per the definitions and classifications in Ryan, Scapens and Theobald (2002), the qualitative section focuses on contextual validity, generalisability and procedural reliability. The quantitative section focuses on internal and external validity and reliability. The section on mixed methods includes validity threats as detailed in Crewell and Plano-Clark (2018), as well as the mitigating strategies employed in the present study.

3.6.1. Qualitative

Contextual validity refers to the extent to which the research has captured the phenomena that it purported to capture (Ryan *et al.*, 2002). Ihantola and Kihn (20011) refers to the authenticity with which the experiences of participants are captured and represented in the research. For the qualitative analysis, this aspect of validity was especially important in the construction of the questions to be included in the interview guide. Creswell and Poth (2016) suggest that researchers carefully consider the motivations for asking each question in the interview. The constructs of bias that we sought to evaluate in this study have their origins in the cognitive psychology literature. Many of the seminal works on behavioural finance were authored by experts in the field of psychology (for example, Tversky, 1973 and Kahneman and Tversky, 1974). Therefore, in order to ensure that the questions for the analyst interviews provided the information on the bias that we intend to evaluate, an expert in the field of cognitive and behavioural psychology reviewed the interview guide to ensure that the questions or discussion themes were not leading, yet still able to elicit the information required to address the aim of the research. The specific rationale for each interview question is detailed in the interview guide.

Since qualitative researchers serve as the data collection instrument during interviews with participants, the research can influence the results of the study by virtue of their initially held perceptions. Creswell and Poth (2016) explain that even though the researcher's collection and interpretation of data from interviews can result in findings that are not entirely objective, this is an inherent characteristic of qualitative research and is not solely a threat to validity and reliability. However, Roberts (2020) suggests that it is essential that they are cognisant of their role and influence. For this study, the researchers did not have any personal interests in the topic at hand. Although they had worked in the financial services industry, they had not served as equity analysts or preparers of integrated reports. Nevertheless, care was taken to avoid leading questions and the prepared interview guide (Table 5: Interview guide) was followed as closely as possible, with equal cognisance not to interrupt the flow of conversation. The researchers have also presented extracts of interviews that ran counter to the identified themes, as suggested in Creswell and Creswell (2017), to provide an objective view of the findings.

In addition to considerations about the researchers' own perceptions, Creswell and Poth (2016) encourage researchers to consider the relationship between the researcher and interviewees. They suggest that the nature of the interviews create "an unequal power dynamic between the interviewer and interviewee" (Creswell & Poth, 2018 p.173). It is therefore suggested that the researcher allow the interviewees an opportunity to question and interpret during the interview. In the current study, participants were asked follow-on questions, such as "what do you think that means about …?". Furthermore, instead of a script of questions in a defined sequence, the interview guide allowed for the interviews to be conversational, thereby reducing the unequal power dynamic.

Generalisability refers to whether the research results can be extended to a wider context (Ihantola & Kihn, 2011). Although the relevance of generalisability to qualitative research has been debated (Creswell & Poth, 2018) it is usually this concern that motivates researchers to include larger numbers of participants. For the present study, the researchers ensured that participants had a range of experience, both in terms of number of years of work as a sell-side analyst and industry coverage. Further considerations regarding the sample of interview participants are detailed in Section 3.4.1.

Procedural reliability in qualitative research refers to the consistency with which the research process was carried out (Ryan *et al.*, 2001). This is similar to the definition from Leedy and Ormrod (2005), where reliability is referred to as the consistency with which an approach will provide a consistent result. The aspect of reliability was especially important at the data collection (interview) and analysis (coding) stages of the study. The researchers attempted to follow the interview guide as consistently as possible in each interview. As discussed in Section 3.4.1 on the format of interviews, the interviews were conducted virtually, on platforms that allowed the recording of interviews or the automatic creation of transcripts. Although the transcripts had to be "cleaned" for instances in which the participants' words were not accurately captured, the transcripts provide an initial measure to reduce errors in capturing participants' responses. The qualitative analysis and findings are presented using rich descriptions, allowing the reader to be "transport[ed] to the setting" (Creswell and Creswell, 2017, p.200). These detailed descriptions of the responses enhance the validity of the findings. In addition, the researcher allowed sufficient time for the collection of data, particularly interview data. Spending a prolonged time gathering insights from practitioners (Creswell & Creswell, 2017) allowed the researcher to develop an in-depth understanding of the cognitive processes involved in the work of analysts and the processes involved in formulating forecasts and recommendations.

Considerations of reliability also informed the coding process. Prior researchers have compared their classifications to those of research assistants or peers who performed the classification independently. Similarly, for this study, the codebook was presented to the supervisor to ensure that the coding was not affected by preconceived ideas of the researcher (Creswell & Creswell, 2017) and that the coding process was performed in a structured and consistent manner. In addition, the use of NVivo software analysis tool minimised the risk of errors that could be made using manual methods of coding. NVivo also enabled the continuous comparison of data with existing codes to ensure that there were no gradual changes to the definitions of codes during the coding process (Creswell & Creswell, 2017).

3.6.2. Quantitative

Internal validity refers to whether valid conclusions can be drawn from the study, considering the research processes. Specifically, for quantitative research, internal validity refers to the extent that variations in the dependent variable result from variations in the independent variables (Ryan *et al.*, 2002). In studies involving structural equation modelling (SEM), internal validity can be assessed using various statistical techniques.

The essence of these assessments is to determine whether the model adequately represents the underlying theoretical constructs and relationships that have been depicted. For SEM, these statistical techniques are applied to assess validity of the measurement model and structural model separately. For the measurement model, indicators of convergent and discriminant validity are particularly relevant. In the present study, factor loadings, average variance extracted, Cronbach alphas and the Fornell Larcker criterion were used to assess validity. Reliability of the structural model was evaluated using indicators of models fit. The results of these validity and reliability gauges are contained in Section 3.4.2 of Chapter 3.

For the quantitative analysis in this study, the integrated report quality is modelled as a latent construct (see Section 3.5.2.). As an additional feature of reliability, the scores were obtained from expert adjudicators of the annual EY Excellence in Integrated Reporting Awards.

External validity, in the context of quantitative research refers to the extent to which findings and conclusions can be extended beyond the specific sample set (Ryan *et al.*, 2002). For this study, a suitably large sample size was used. Data related to various companies and extended over a period of six years.

3.6.3. Mixed Methods

The preceding two sections detail the steps taken by the researchers to ensure validity and reliability of the respective qualitative and quantitative aspects of the present study. In addition, the study incorporates the suggestions of Creswell and Plano-Clark (2018) to ensure validity in the mixed methods approach. This is done to ensure that correct inferences are drawn from the integrated data.

One of these strategies includes creating parallel ways of examining the same concept. In the present study, the researchers created parallel ways of examining each bias. In the qualitative analysis, interview questions about each bias were developed from the prior literature. In the quantitative analysis, each bias was represented by a set of measurement approximations.

The validity of the underlying thematic classification scheme of the data is a function of the researcher's knowledge of the area being investigated (Leedy & Ormrod, 2005). Creswell and Creswell (2017) suggest triangulation of different data sources as a validity strategy. In this study, the results are based on converging quantitative and qualitative sources of data. Jick (1979) discusses the benefits of the mixed methods approach, given the strengths and weaknesses found in single method designs. Triangulation is a metaphor from navigation and military strategy whereby several reference points are used to find an object's exact position. Similarly, when researchers use multiple kinds of data on the same phenomenon, the reliability of their findings is improved. In this study, measurement approximations were created from empirical data for the behavioural biases and data on the biases was also collected from the interviews. This mixing of methods and triangulation of methods and data contributed to the validation and interpretation of statistical results. They also helped understand puzzling findings, thereby enabling a more holistic interpretation of the findings (Creswell & Plano-Clark, 2018).

3.7. Chapter Conclusion

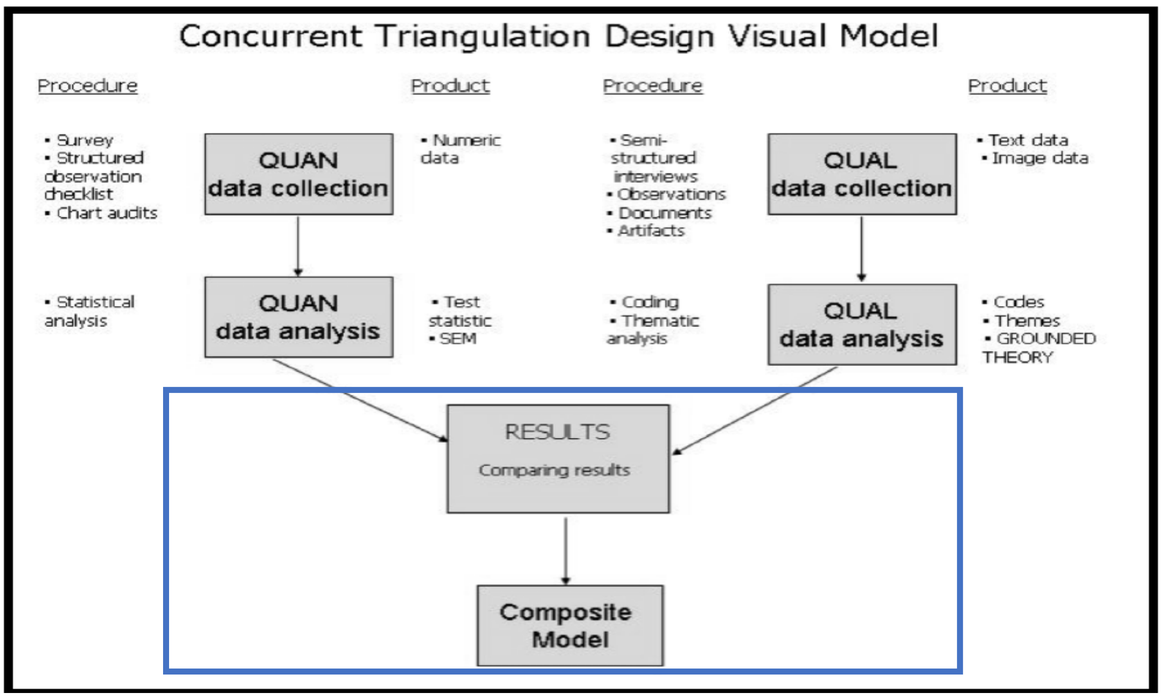
In this chapter, the methodology, which incorporates qualitative and quantitative analysis was detailed. The concurrent design in Figure 7 was introduced as a guide to each step in the research process. The qualitative component involved the interviewing of sell-side equity analysts, coding the transcripts and identifying themes. A measurement model was created with measurement indicators for the latent constructs of the biases and integrated report quality. A structural model was used to test the hypotheses. Detailed consideration was given to ensuring the reliability and validity of the quantitative and qualitative data and analysis and mixing of methods. The results of the analyses are presented in Chapter 4.

Chapter 4: Results

4.1. Introduction

This chapter presents the findings of the qualitative and quantitative analyses separately, and then synthesises the results from each set of data, as suggested in Creswell and Plano-Clark (2018). We return to Figure 7: Convergent Design. In this chapter, the outputs of the quantitative and qualitative data analysis are combined, and a "composite model" is presented in the latter sections of this chapter. By combining qualitative interview themes with quantitative trends and patterns, a holistic interpretation is provided in the composite model.

Figure 7 Convergent Design



Source: Creswell and Plano-Clark (2018) as adapted in Carmichael (2020)

The chapter proceeds as follows. Section 4.2. details the results of the coding process of interview transcripts. Section 4.3. provides descriptive statistics and the results of the measurement and structural model. The latter sections of the chapter contain a joint depiction of the results of the qualitative and quantitative analyses.

4.2. Results: Qualitative Data Analysis

4.2.1. Interview themes

Details of the coding and categorisation by themes is contained in Chapter 3.5.1. In this chapter, the themes are discussed in detail and related to prior literature.

A summary of the themes and the number of participants whose responses were used to develop them is provided in Table 10. Each theme is then discussed in detail, with illustrative quotations in the rest of this section.

Table 10: Summary of themes

Theme	**Number of participants**
Key themes	
Use of integrated reports	20
Impact of audit failures	20
Availability bias	17
Overconfidence bias	17
Loss Aversion bias	17
Herd behaviour	20
Analysts' incentives	16
Additional themes	
Company protocols	12
Interaction between buy-side and sell-side analysts	5
Difficulties in the sell-side equity research industry	4

4.2.2. Use of integrated reports

The interviews indicate that analysts prefer to use the financial statements (annual reports) and/or the summarised financial statements contained in SENS announcements. Integrated reports were occasionally consulted although they served a confirmatory purpose, rather than the initial foundation of the analysts' models, for several reasons. Participant 16 had worked in a private equity company and had performed valuations on unlisted entities in the past. They reflected on the availability of information for listed and unlisted firms and concluded that there was no difference in the information from either type of firm. Notably, unlisted entities are not required to produce annual integrated reports.

The present research therefore affirms the findings in notable prior research (Holland, 2006; Rensburg & Botha, 2014; Willows & Rockey, 2018). According to the results of an online survey, very few stakeholders used the integrated report as their primary source of information, but rather considered it supplementary information to other sources (Rensburg & Botha, 2014). Our results are also consistent with those of the event study by Willows and Rockey (2018), where the market reaction to the release of the annual financial report was found to be stronger than the reaction to the release of the integrated reports. The authors posit that the information in the integrated report is already priced into the share by the time the report is released.

A key advantage of data collection via semi-structured interviews in this study is that the views of a group of primary users of financial information could be obtained directly. Therefore, although our findings appear to merely confirm those of prior research, we are able to provide specific reasons for the lack of use of integrated reports, directly from the analysts' perspectives.

Detailed financial information found in annual financial reports is commonly used as the basis of analysts' forecast models. These models are updated quarterly or more frequently, depending on the macro-economic environment or significant changes in the company's operations. According to Participant 4, a recommendation revision could be triggered by "anything material that has happened that could impact either the financial or business model". The theme of frequency was further emphasised by another participant who explained that sell-side analysts are incentivised to have their recommendations as up to date as possible. They said:

"[It] goes back to the motivation that we're paid to put out information frequently."

- Participant 8

However, integrated reports are produced only annually whilst trading updates are issued quarterly (JSE, 2019), and interim financial reports provide a view of the financial results half-way through the financial year. The mismatch between the frequency of the release of integrated reports and the frequency with which analysts update their forecasts is one of the reasons for the use of the former for confirmatory purposes.

In addition, the delayed release of integrated reports after financial year end is another reason for analysts' preference for the timelier trading updates and annual financial statements. Companies are only required to release their integrated reports three months after the end of their financial year (JSE, 2019), whilst annual reports and trading updates on SENS are required more frequently, each quarter. It is partly due to this delay that the information contained in integrated reports is not "new" by the time it is released. This frustration was communicated by Participant 1 who explained that "the information is just [pauses] too [pauses] old". Participant 3 explained that they read the Chairman's report and the CEO's report but that the reports had not contained any information that was not known by the analyst by the time the report was released.

Despite the use of financial information in the annual reports, analysts unanimously cited the established limitation of the historical focus of accounting information. There are different sources of information that are used to compensate for the historic focus of the financial reports. These findings are aligned to the findings of Coleman (2014) who found that practitioners did not use certain finance theories because the latter ignored data that is available to the practitioners. These findings were in the context of the lack of use of neoclassical investment theory in the real world. Yet, they appear strikingly similar to the findings of this study, in the context of the usefulness of accounting information.

One of the strategies that analysts use to supplement fundamental analysis on less recent data is the use of technical analysis. Participant 1 explained that they "default on technical analysis" as the market incorporates more recent information that is not contained in the annual reports or the integrated report. Participant 1 covered shares that were listed on the JSE and shares that were listed on the London Stock Exchange and the New York Stock Exchange. The analyst explained that technical analysis was relatively easier to perform on international shares due to the, "availability of information". Echoing this sentiment, Participant 20 bemoaned the "liquidity and [lack of] participation" on the JSE. They explained that it was difficult to build a "strong" historic dataset of share price information if they want to analyse a "different" company, that has not attracted a substantial analyst following. It appears that the inherently historic focus of accounting information, notwithstanding the intention of integrated reports to provide information to enable investment decisions (IIRC, 2021), can lead analysts to place more reliance on technical analysis. The technical analysis, in turn, is inhibited by illiquidity in the JSE, according to the participants. This issue is further explored later in this chapter, under the section, “Difficulties in the sell-side equity research industry”.

Participant 9 explained that they were not a Chartered Accountant and explained that they had difficulty in interpreting the information in the financial reports. Despite being an experienced analyst with a thorough knowledge of the sector that they covered, they often had to consult with accounting professionals to understand, for example, whether to exclude certain line items from their forecasts. Other analysts who did not have an accounting-focused tertiary qualification expressed the same frustration. Interestingly, an experienced Chartered Accountant, Participant 12, supported the view of the non-accounting professionals. Participant 12 had noted the difficulty that her colleagues had experienced in relating the various accounting line items to each other to construct a narrative around the numbers. This participant also felt that “perhaps the accounting is getting too complicated”. This sentiment echoes that of Joffe (2020) and the research from Pascual-Ezama *et al.* (2018) that even skilled investors have difficulty in interpreting certain financial information. Their call for corporate reports to be shorter and simpler is particularly relevant, given the difficulties expressed by the participants.

There is no dearth of literature on impression management in the integrated reports (see for example, Melloni, Stacchezzini and Lai, 2016). On this issue, one analyst took the perspective of information asymmetry.

And you know the integrated report is information that the company wants to show you. But if there's something that's not great, they will gloss over it. It will be disclosed in a note somewhere where you've got to make sure you read 200 pages of the report to find it.

- Participant 8

Participant 1 echoed a similar sentiment when they complained about the “lack of consistency” of integrated reports. When questioned further, the participant explained that the inconsistency was not related to the application of international financial reporting standards but rather “in the way in which management speaks about certain key strategic issues”.

A fundamental difference between the analyst reports and the integrated report is the inclusion of sustainability-related information in the latter. This type of information would be especially important when forecasting future share price performance. Coleman (2014) found that fund managers followed an “integrated investment process that incorporate[d] macroeconomic, industry and firm features” (p. 235). In this study, all participants acknowledged the importance of “ESG”. However, the information on a company’s ESG practices was obtained during discussions with management instead of from the integrated report. Yet, the integrated report is meant to provide information on the use of various forms of capital in the creation of sustainable value (IIRC, 2021). When asked about their use of integrated reports specifically, only Participant 19 reported reading extracts from the integrated report in preparation for the discussions with management. This practice was summarised by them as follows:

Key risks are often given in integrated reporting both from an HR perspective and from an operations perspective which gives you a great view of the company. I like looking at things like *employee turnover rates - why did you lose 20% of your staff in this year…. Those are the kinds of information that you get out of the integration report that you could just ask management.*

- Participant 19

Notably, at the management meetings, analysts gather information based on how management communicates and the dynamics between members of the management team. For these cues, the analysts relied on their "gut feel" or mental heuristics. In the context of meetings with management, Participant 8 explains, "It'll be difficult to put it in a report and to prove it, but it's gut feels." Extending the notion of "gut feel", the same participant, later in the interview said, "I personally will only recommend the stock if I've met management. It goes back to the thing that I mentioned earlier - that trust element. Like, can you trust what they're saying to you?". The perceived trustworthiness of management was a notable finding in the research by Newman *et al.*, 2013. Their research focused on buy-side analysts and used a PLS structural equation model. They assert that buy side analysts "feel good" about companies with management that they trust but may not necessarily invest in them for that reason alone (p.142).

Participants were of the unanimous view that meetings with management were a key source of information about the company. In the context of fund managers in the United Kingdom, Holland (2006) also found that although the financial reports were an important source of information, it served as the starting point for creating further questions for management. The further questions for management related to non-financial variables such as strategy, financial plans and management style. The similarity of these findings to those of the present research are notable as the United Kingdom is considered a developed economy whilst South Africa is a developing economy, possibly with different levels of information flows.

Similarly, Drachter *et al.* (2007) found that discussions with executive management are the most important source of new information to fund managers in Germany. The present study finds that in these discussions with management, analysts relied largely on their perceptions and judgement. Heuristics or gut feelings are applied when evaluating management's assertions directly, about their assertions regarding the future prospects of the company and indirectly; about whether the dominance of specific executive managers is likely to be mediated by the rest of their team. The findings in the present study echo those of Coleman (2014) where the contribution of less quantifiable aspects, such as organisational culture, managerial skill and governance were considered with equal gravitas as fundamental and technical factors.

The importance of meetings with management is intriguing, given the research titled "Sell-Side School Ties" from Cohen, Frazzini and Malloy (2010). Analysts were found to outperform their peers by 6.6% per year (referred to as a "school tie premium") when they had an educational link to the company that they covered. Educational links were defined as attendance at the same educational institution. The research highlighted the value of social ties in the sell-side research industry. This point was raised incidentally by Participant 7, when they referred to the importance of "skinner", an Afrikaans word meaning "gossip". When the participant was probed further, they went on to explain the importance of access to management. Notably, Cohen *et al.* (2010) also examined the mediating effect of Regulation Fair Disclosure (Reg FD)[13] on the

[13] Regulation Fair Disclosure (Reg-FD) is a regulation from the United States Securities Exchange Commission that was enacted in 2000. Amongst its primary objectives are the promotion of fair access to corporate information (Brown *et al.*, 2014).

performance of connected analysts relative to their non-connected peers. The study found that after the enactment of Reg-FD, the school tie premium was almost zero. Notably, in a South African context, Esterhuyse (2018) used the JSE Listing Requirements as a motivation for the study of information provided on companies' investor relations websites. The study found that there was an information advantage to attending and participating in investor presentations, as companies rarely provided transcripts, audio or visual recordings of the interactions. This evidence, together with the results of the present study's interview analysis, highlights the potential for corporate reports to mitigate information advantages gained through social networks or other opportunities for interaction with management.

In summary, it is evident that analysts gather information from various sources and combine them to create their forecasts. With these findings, the present study affirms the findings of Brown *et al.* (2015, p.20), that a "mosaic" of inputs is used by analysts as they formulate their recommendations. We extend these findings by highlighting the key sources of financial information that analysts use and how they are used to develop recommendations. Accounting information in the financial statements is a key source of information, despite its historical focus and relative infrequency. The detail in the integrated reports is consulted intermittently for confirmatory purposes. By far the most important source of information was discussions with company management, both for direct, specific information and to create a "gut feel" for the reliability of the management team. This theme has implications for other strands of research. The investor relations research focuses on the company's communication with investors. As detailed in Section 2.2, investor relations research in South Africa has considered the use of various platforms by investor relations teams to communicate information to investors, as well as the implications of these communications for firm value. The present study's findings suggests that the dialogic communication[14] is highly valued by analysts. In an American context, Brown *et al*. (2015) found that private communication with management was considered by analysts to be more useful than their own primary research. The present study's findings suggests that there are interventions of judgement (which may include heuristics) which occurs between the stage of obtaining information from management and deciding whether to prioritise it over other forms of the analysts' own research.

4.2.3. Impact of audit failures

There was unanimous agreement amongst the participants that accounting irregularities had influenced their view of accounting information. They appear to maintain a "healthy dose of scepticism" (Participant 4).

*I've always been sceptical [pauses] not cynical, mainly sceptical because it's extremely difficult to audit some of these very complex multinational companies such as ***. And so it's very difficult to have a high degree of conviction on the quality of the audit to begin with, so I've always been a little bit sceptical. I would be lying if I said it had zero effect as to how I looked at companies afterwards also. I scrutinise them just that little bit extra to be sure. But I would expect a lot of analysts to have a healthy dose of scepticism, any good analyst would.*

- Participant 4

[14] Explained in Brennan and Merkl-Davies (2018) as a two-way form of communication

The impact of audit failures on the investment process appeared to be twofold. Firstly, in the way in which analysts verify the correctness of information and secondly, in the incorporation of scepticism in their valuation models and forecasts.

There was acknowledgement that a detailed re-audit was not possible but, as with the deficiencies in integrated reports, the analysts had adapted ways to further scrutinise the accounting information. Corroborating evidence was gathered in various ways. As part of the usual investment process, analysts performed detailed analysis of ratios from fundamental information. Whilst these ratios are used to forecast inputs such as sales and cost growth rates, the ratios are now also used to confirm accuracy of the subject company's accounting information. This is done through detailed comparisons with peer companies, research conducted by analysts "in the field" and in discussions with management.

As an example of research conducted "in the field", Participant 1 explained that they visited the stores of a retail group that they covered to get a sense of the foot traffic through those stores. They enquired from delivery personnel regarding the frequency of re-stocking in the store compared to competitor stores. Similarly, Participant 7 detailed how they had visited the factories of one of the companies that they covered.

As detailed earlier in this chapter in the section titled "Use of integrated reports", the discussions with management served to form an opinion on the trustworthiness of the information presented, even to assess the likelihood of accounting irregularities. Participant 6 described their experience of covering a company in which accounting irregularities were subsequently uncovered:

*The financial statements were fine. There wasn't any issues in there. There was, issues in terms of the dominance of the previous CEO being ***, which bothered us....And so those are some things you don't really get from the numbers because I mean maybe the audit firms might have followed whatever processes they followed, and all of the numbers checked their own internal process. I'm not saying that audit firms were complicit or negligent in their analysis of ***. But it didn't feel right to us. And so for us we applied a higher cost of capital to their business.*

- Participant 6

Increasing the cost of capital was a common way of accounting for the increased risk of accounting irregularities, as perceived by analysts. This perception was based on the analysts' judgement. Following an audit scandal, Participant 7 explained that they "took extra care" when analysing companies for which the same audit firm was responsible. In addition, Participant 1 flagged the directors of the board where accounting irregularities were uncovered – "we check where else these directors are working and we tend to be more aware of that – our research is more rigorous".

In contrast, research in the US context showed that analysts tend to take the financial statements as they are because they have faith in the audit process (Brown *et al*., 2015). In the study, the interviewed analysts explained that if the auditors could not detect misrepresentation, then it was unlikely that the analysts would. In fact, even highly-regarded analysts did not see it as a priority to consider the possibility of misrepresentation.

4.2.4. Availability bias

As detailed in the literature review, individuals display the availability bias when they overestimate the likelihood of an event based on the ease with which the events can be recalled. The ease of recollection is in turn influenced by the amount of information available and how vividly previous instances can be recollected. Each of these factors which influence recollection were applied in analysing interview transcripts.

Regarding the amount of information available, ease of recall can be influenced by media coverage relating to a firm. This could cause analysts to focus on information that is easier to access and understand rather than basing their forecasts on a balanced view of information about the company. Jang and Ho (2022) used institutional ownership as a proxy for analysts' familiarity with companies that they covered. They posit that when a firm has a higher proportion of institutional shareholders, there is more likely to be more thorough oversight and improved access to information, which will lead to enhanced transfer of information. Analysts were therefore asked whether it was easier to cover companies which had greater institutional ownership, received greater media attention, or had a greater analyst covering. None of the analysts had found it particularly easier to cover these types of firms. Participant 1 explained that they ensured that they were aware of coverage of their subject companies in "business media" but that analysts "could be wrong" if they base their decisions on media coverage.

Regarding the vividness with which events can be recollected, the topic of audit failures and financial misstatements was discussed. Regarding the audit process, Participant 4 explained that they had "always been sceptical". This analyst's view was relatively unique in that their scepticism pre-dated more recent instances of audit failures and financial misstatements. Other analysts appear to have developed this scepticism. For example, Participant 10 explained that the "negative selection pillar" was incorporated into the research process "over the last few years". This may suggest availability bias in incorporating audit failures in forecasts.

Some analysts appeared to be more acknowledging of the manner in which audits are carried out and the inherent limitations of any audit engagement. Participant 3 felt that having the same board of directors or auditors did not justify further interrogation of the accounting information – "auditors can't detect fraud in all instances – you shouldn't adjust companies that were not affected – that's when you're being biased". They thought it would be unlikely that audit irregularities would become more frequent. This view was in contrast to the relatively harsher stance taken by other participants in the study and warranted further investigation. Participant 3 further explained that they had not been directly or indirectly involved in the coverage of any companies that had been affected by audit or accounting irregularities. This may suggest that the perception of increased risk of audit or accounting irregularity may be influenced by the analysts' personal experience of such events in the companies that they cover. It is consistent with the explanations of availability from the seminal literature. Individuals exhibit the availability heuristic when they judge the likelihood of an event based on the ease with which similar past events can be recalled (Tversky & Kahneman, 1974). The availability heuristic can lead investors to overweight current conditions in their forecasts (Lee *et al.*, 2008).

The analysts interviewed for this study had differing educational backgrounds. Participants 1, 4, 6, 7,8, 11 and 20 had Science, Mathematics and/ or Actuarial qualifications. Participants 3, 12, 13, 15 and 19 were Chartered Accountants who had been trained as auditors. The latter participants appeared to be more acknowledging of the manner in which audits were carried out. For example, Participant 15 explained, “Look if you are an accountant and you’ve come from the audit firm and you know all about sample testing. You know it’s possible for there to be fraud”. However, Participant 8 appeared to be the outlier in this apparent trend. They had not worked at an audit firm and yet they said, “When you go back to kind of first year articles, you know there are horribly underpaid, horribly overworked so it's incredibly, incredibly difficult for the auditors to pick up fraud”. As the interview progressed, it transpired that a close personal relative of Participant 8 was a Chartered Accountant who had worked in an audit firm. Collectively, these insights may be interpreted as depicting that familiarity with the audit process can influence the reaction of analysts to accounting and / or audit irregularities.

The insights from the interview process appear to indicate that analysts prioritise the most current information. However, they do so to incorporate the current business environment as they need to form a view on the future prospects of their subject companies. It is in the estimation of the likelihood and potential impact of audit irregularities that there appears to be a heightened awareness due to recent corporate scandals and related personal experience.

4.2.5. Overconfidence bias

Overconfidence refers to a cognitive bias where individuals tend to have a higher level of confidence in their judgements than can be justified by their actual skill levels. As detailed in the literature review, this bias can manifest in many ways. This section details these manifestations (or lack thereof) from the interviews with the analysts.

One of the manifestations of overconfidence amongst investors is the belief that one is able to identify opportunities for arbitrage more accurately than one’s peers, despite all investors having access to the same information (Barber & Odean, 2001). In other words, overconfident investors tend to feel that they can make better decisions based on the same information. They trade more actively and more speculatively and hold more undiversified portfolios than their peer investors (Barber & Odean, 2001).

The present study finds that analysts tend to rely heavily on discussions with management for information about the company (see earlier discussions in this chapter under the section titled “Use of integrated reports”). Drachter *et al.*, (2007) found that information gathered from management by the fund manager dominated investment theory when making investment choices. In addition, Drachter *et al.*, (2007) found conversations with other fund managers were deemed to be important while the actual investment decisions of their peers were not. The authors posit that this is evidence of fund managers’ belief that they are able to make better decisions than their peers based on the same set of information, just as described in Barber and Odean (2001). Applying the assertions of Drachter *et al.*, (2007) to this study, it appears that the dynamic whereby critical information is obtained from discussions with management is likely to increase proclivity to overconfidence, as analysts overweight their inferences from this information.

Another manifestation of overconfidence is the illusion of control. Overconfident individuals are likely to believe that they have more control of outcomes than they actually do (Barber & Odean, 2001). Furthermore, they tend to attribute positive outcomes to themselves and negative outcomes to factors beyond their control (Hilary & Menzly, 2006). Analysts were asked what factors contributed to their accurate forecasts. It is conceivable that an analyst attributes positive outcomes to themselves if they had an internal locus of control and not necessarily because they were overconfident. According to Rotter (1966), individuals with an internal locus of control perceive outcomes as contingent on their behaviour or their own abilities or characteristics. On the other hand, those with an external locus of control perceive outcomes as contingent on chance or outside of their control. Importantly, these perceptions of cause and effect have been shown to be equally applicable for both positive and negative outcomes (Rotter, 1966). Therefore, it was important to ask participants about the factors that contributed to their inaccurate forecasts as well, and to gauge the differences in perceptions of cause and effect for each situation.

Participants attributed accurate forecasts to their own forecast models, their hard work and experience. They rejected the notion that these forecasts happened by chance. Conversely, they attributed inaccurate forecasts to unforeseeable changes in the economic environment or the inability of company management to execute on their plans. Participant 9 explained, “we live in an environment that is rapidly or constantly changing. Immediately. You put your model down, there's new information coming through, or that's developing in the market that actually will render your model completely out.” Participant 10 cited discussions with management:

Everyone sort of sticks to what management says about what the range is supposed to be. But I think the one thing that everyone forgets is that like them, management is waiting to see how the year plays out and how a lot of variables play out.

- Participant 10

Participant 6 had worked as an analyst in the past but had recently assumed a role in a smaller financial institution in which they lead a team of researchers. This participant described that there were “massive egos that tend to work in these types of industries”. In the context of marketing the sell-side analysts’ research, Participant 20 explained that “when you walk into the room, the client must want to know what you have built [in your models]” and “there is a certain charisma, an x-factor.” In explaining the characteristics of a good sell-side analyst, Participant 13 said, “this is a confidence game”.

At the end of each interview, the researcher posed an open question to the participants by asking if there was anything else they would like to add or for the researcher to consider. Participant 9 asked if the researcher was satisfied with their responses. The researcher re-affirmed that there were no right or wrong answers and that they were very grateful for the participant’s time. The participant went on to explain the difficulties that they encountered when they started their career as a sell-side analyst. The analyst explained:

I think part of the reason that being an equity analyst is difficult for women in particular is that boys generally tend to be more confident about their thoughts…. But women, we tend to be a lot more uncomfortable with not being certain.

- Participant 9

They went on to explain that their colleagues were more confident, even if they were uncertain of elements of their forecasts. These observations are consistent with the research that shows that in areas of finance, men tend to be more overconfident than women (Prince, 1993; Barber & Odean, 2001).

The insights from the interview process show little connection between report quality and overconfidence. There is however, strong evidence to indicate that analysts tend to overweight their own ability to achieve accurate forecasts whilst inaccurate forecasts are attributed to factors beyond their control.

4.2.6. Loss Aversion bias

Participants generally adopted a more conservative approach when there was any uncertainty regarding the quality of accounting information from the company. They incorporated a "risk premium" (Participant 12) in their financial models to account for the increased uncertainty.

As discussed in the literature review, loss aversion manifests as analysts require a greater quantum of decrease in the earnings of firms before they are added to a strong sell list than the quantum of increase required for the stock to be added to the strong buy list (Asquith *et al.*, 2005). This implies that analysts are more reluctant to issue strong sell recommendations than they are to issue strong buy recommendations. In the interviews, analysts were therefore asked to explain the criteria that must be met before a downward revision is issued. This was contrasted to the criteria for an upward revision.

The criteria for upward and downward revisions appeared to be dictated by the protocols of the analysts' employer. Participant 20 explained that the criteria were deterministic. Similarly, Participant 2 described that they needed to "take a house view" when finalising their recommendation revisions. Participant 1 had experience with both the sell-side and buy side research. They described that in order for a company to buy a stock, it would need to increase by a greater amount than the amount that a stock would need to decrease before it was sold. This was a somewhat contrarian view. The participant explained that this was the stance from the buy-side and not the sell-side. From the perspective of the sell-side analysts, Participant 4 explained that revisions would be triggered by the same types of events, irrespective of them being upward or downward revisions. They explained:

There are two things that we look at…[firstly] price movements. The second would be a change in the outlook. So anything material that has happened that could impact the either the financial or business model.

- Participant 4

However, it emerged that there was a reluctance to issue downward revisions unless absolutely necessary. Participant 2 explained:

"You revise upwards more than you do downwards. The stock would have to move very, very highly against the house view for it to become a sell. It's easier for it to move into buy territory then it is to move into sell. You'd rather place a hold recommendation or even a neutral recommendation before you go down to sell".

This reluctance towards downward revisions could be a manifestation of loss aversion. It may also be reason for the observation of Barberis, Schleifer and Vishny (1998) that institutional investors respond more strongly to downgrades than to upgrades. Institutional investors are likely aware that downgrades are less frequent and issued only when absolutely necessary. They are therefore more likely to react to the downgrades rather than the upgrades.

However, the reluctance to issue downward revisions could also be indicative of the incentive of sell-side analysts to issue positive recommendations. The incentives for these positive recommendations are detailed later in this chapter, in the section titled "Incentive conflicts".

4.2.7. Herd Behaviour

As detailed in the literature review, herding refers to the bias where individuals ignore relevant information and base their decisions on the actions of other analysts. Specifically, the motivations for herding in the capital markets has been attributed to an agency problem, where an agent is incentivised to convince a principal that they are right (Banerjee, 1991). In the context of this part of the study, the agents are the analysts and the principals are their clients.

Participant 14 had strong views that the practice of herding was inherent in the work of the sell-side analyst. During the interview, they shared their screen on Ms Teams and opened the Bloomberg portal. They pointed out that analysts usually released their recommendations at around the same time. The researcher questioned whether the release of recommendations rather coincided with the release of annual results or trading updates. The participant acknowledged this assertion but further explained that in their experience, it was usually the more experienced analysts who released their results earliest, with other analysts following soon thereafter.

The participants were asked how, if at all, they establish reasonability for their forecasts. Almost all of the analysts interviewed explained that they checked the Bloomberg consensus forecasts before releasing their recommendations. This supported the assertions from Participant 14. However, this response was usually provided in a positive light, in the context of explaining a rigorous research process, in which the information content of prior analysts was considered. The analysts used the broker consensus as a source of information. This practice is consistent with the sequential decision model analysed by Banerjee (1992). In a sequential model, each individual considers the decisions of previous decision makers, as they may have some information that is relevant. In such a situation, the authors show that the resulting equilibrium will be inefficient. For example, Participant 3 explained:

I use the broker consensus to try and see if I'm not going haywire or if there's something else that is happening that I don't know about. If I'm looking at the broker consensus and they all take the target price to be "x" then I try to focus on what I'm doing differently.

- Participant 3

Participant 10 explained how they react when their forecasts are different to the consensus. They explained:

[The broker consensus] is something that I can constantly benchmark myself against. Like where is the target price, you know, and then you go back into your model and then try to tweak the growth rate and tweak this and tweak this just so you get as close as possible to where the rest of the group is.

- Participant 10

Similarly, Participant 11 combined the information from broker notes with their own information on the company ("growth prospects") and the business environment ("business cycle").

The focus of many prior studies is to find the reasons for herding (Scharfstein & Sten, 1990; Banerjee, 1992; Gu *et al.*, 2022). The present study focused on integrated report quality. Participant 1 explained that the broker consensus is a very important part of the technical analysis part of their processes because it was new and was likely to incorporate most recent information. None of the analysts attributed herding directly to poor quality accounting information.

In order to mitigate the possible effect of the researcher's pre-conceived notions (Creswell & Poth, 2016; Roulston & Choi, 2018), the semi-structured interviews incorporated the open-ended question about establishing reasonability for their forecasts. It emerged that there are important reputational motivations for herding, both with their peers and to their own prior recommendations. Participant 14 explained that sell-side analysts are "the only profession where your performance is ranked publicly [as part of the annual Financial Mail Analyst awards]". In explaining the process for revising recommendations, Participant 20 explained that despite the process being "deterministic" with regards to the change in target share price, that analysts tended to be reluctant to deviate too far from their initial recommendations. They went on to explain that changing a recommendation also carried the reputational risk of having to explain why their initial recommendations were incorrect, if for reasons other than changes in the company's prospects. It appears that the proclivity to herding is motivated largely by reputational reasons. These notions appear to echo the sentiments of Keynes (1936 p. 157 - 158), as cited in Scharfstein and Stein (1990) – "it is better for reputation to fail conventionally than to succeed unconventionally".

Participant 4 was one of the few analysts who did not check the broker consensus until after they released their forecasts. They explained:

Not at all. That may not be the answer you get from everyone. I usually do all my analysis and only afterwards would I look, once I've published my note to see what the market is thinking. And the reason was I didn't want to be influenced by the other brokers and I didn't want to model to a number if that makes sense? Because then how honest are you really being with yourself? Then you've got zero differentiation. Just serve the same numbers of anyone else.

- Participant 4

Notably, this analyst had won an award in the Financial Mail Analyst Awards. Participant 15, who had also won an award in the same competition explained that they also did not check the consensus until after they published their notes.

Although they checked the broker consensus, "for reasonableness", Participant 12 had the strength of their convictions to sometimes ignore the consensus. They explained, "But if I have very strong views, I don't always take the consensus in[to account in] my numbers. Remember that if they [analysts] haven't updated for the GDP shock that came through last week, then the numbers [on Bloomberg] are incorrect." Participant 12 was of the view that the sell-side research industry in South Africa was shrinking and therefore there were not as many forecasts contained in the broker consensus. These insights are detailed later in this chapter, in the section titled, "Difficulties in the sell-side equity research industry". A comparison of the insights from Participant 12 to the insights from the majority of analysts interviewed, it is apparent that there are varying extents of herding, as identified in Banerjee (1992). On the one extreme, agents abandon their own signals even when they are not entirely certain that the other individual is correct. A less extreme version of herding was demonstrated by Participant 12 – the broker consensus was consulted but changes to their own forecasts were not always deemed necessary.

Overall, the insights from the interviews reveal that analysts do not herd directly because of uncertainties regarding the quality of accounting information. However, the practice of herding seems prevalent as analysts use the broker consensus as a source of recent information about the companies they cover. In such situations, Bannerjee (1992) suggests that markets may be better off by constraining certain decision makers to use only their own information.

4.2.8. Analysts' incentives

Very early on in the interview process, it became apparent that sell-side analysts rely heavily on their discussions with company management to make informed forecasts. Participant 10 was a buy-side analyst at the time of the interview, having worked as a sell-side analyst in the past. They emphasised the inherent reliance on company management.

I'm now on the buy side - on the sell-side, you really do rely on management and being in management's good graces. So you try to toe the line as much as possible.

- Participant 10

Participant 12 discussed how the reliance on management could extend to a lack of objectivity.

I think for sell-side analysts, the access to the management team is absolutely key, absolutely important…In a way the sell-side research is an extension of management's thoughts.

- Participant 12

The conflict created by the reliance on management echoes the findings of Brown et al. (2015) – analysts who issue unfavourable recommendations face the risk of being excluded from future question and answer sessions with management. In an emerging market context, Chaudhury *et al.* (2022) provide further support for this notion. They explain that sell-side analysts forecast are biased due to the need to create good relationships with management of the companies that they cover. Buy-side analysts therefore temper their reliance on the research from the sell-side analysts because they are aware of the sell-side analysts' need to maintain good relationships with company management.

For the purposes of this research, the quantitative analysis includes only recommendations from non-sponsored research. None of the interviewed analysts covered companies who had commissioned their own research. However, the issue remains relevant for this research as it points to a phenomenon that has the potential to encourage overly optimistic research by analysts.

The methodology for the annual Intellidex Financial Mail Analyst competition is explained in a special report in the Financial Mail (2023). Domestic institutional clients are asked to rate sell-side analysts through a confidential online questionnaire process. The survey is developed by the Financial Mail and Intellidex teams. Prior to compiling the questionnaire, Intellidex requests that the institutional brokers submit a list of the sell-side analysts whose research they use. Respondents are asked to rank the five best firms and the five best analysts respectively. The following criteria are used: quality of written fundamental research in terms of content and value, accuracy of forecasts and buy/ sell recommendations, useful ideas, effective communication and consistency over the past year.

Participant 20 explained that analysts need to be aware that their clients are asked to vote in the awards – their clients may not provide a favourable perspective if they have incurred a loss based on the analyst's recommendation. These sentiments are supported by the seminal work of Hong and Kubik (2003), which discusses a similar annual poll conducted by the Institutional Investor magazine. The two most important evaluation criteria for the poll are perceived expertise in earnings forecasts and stock picking. The existence of these types of incentives shows that despite the possibility for optimism, the perceived quality of the sell-side analysts research is a key determinant of career progression. It is therefore unlikely that optimism or lack of independence is the sole motivator for analyst forecasts.

Acknowledging this, Hong and Kubik (2003) control for analysts' accuracy in their model. They find that analysts who issue more optimistic forecasts are statistically more likely to move up the brokerage hierarchy. Furthermore, the study shows that for career progression, analysts are judged less on accuracy and more on optimism when it comes to coverage of shares affiliated with their brokerage houses.

During the interviews, the theme of declining analyst coverage emerged. In response, corporates have begun to commission or sponsor research by sell-side analysts where they are the subject of the research. Issuer sponsored research or commissioned research is different from the traditional service model of equity research where research is paid for by the potential investor or company using the information for decision-making. The rising trend of commissioned research is also discussed in the section on "Difficulties in the sell-side equity research industry". Given the reliance of analysts on company management for information as well as the themes of analyst incentivisation in this section, the sponsoring of equity research by the subject company has implications for analysts' incentives to issue overly optimistic reports.

4.2.9. Additional themes

The open-ended structure of the interview questions allowed for the emergence of themes in addition to those anticipated from prior literature. These themes became apparent during the inductive coding in the first round of coding, in the second round of coding and when grouping apparently outlying codes. It was important for the researcher to capture and code these parts of the interview transcripts to ensure that the researcher's preconceived notions (if any) would not compromise the presentation of a complete and balanced reflection of the interview process (Creswell & Poth, 2016; Roulston & Choi, 2018). These themes are discussed in the sections that follow.

4.2.10. Company protocol

During the interviews with the analysts, it emerged that the process of formulating a forecast was, to a large extent, according to the prescribed guidelines from their employers. The existence of these protocols was not specifically asked for in the interviews but was consistently discussed in the introductory, tour question about how the participants went about formulating a recommendation and target price. Phrases such as "it typically starts the same for every company that *we* look at…" (Participant 10) and "*our* process ends with preparing a written recommendation or presentation" (emphasis added) (Participant 8). Participant 7 explained that “we’ve created this hybrid process…” and Participant 6 referred to “a very disciplined, qualitative process”. Participant 19 summarised the use of established processes when they used the phrase “besides going through the basics of…” in the following extract:

We go through a lot of processes and each analyst has their own process for their sector that they prefer, besides going through the basics of reviewing all of the company financials and integrated reports, building yourself a comprehensive model that you feel is capable of capturing your intrinsic value.

- Participant 19

The guidelines appeared to be sufficiently flexible and covered “the basics of” the forecasting processes. The flexibility allowed each analyst to incorporate their own nuances and techniques in the process. These nuances appeared to differ depending on the industry that the analyst covered – “And then I think one of the areas that sort of differs, is some analysts will have lots of industry information that they have at their fingertips, some don't.” (Participant 19). In describing the attributes of a successful analyst, Participant 20 cited the analysts’ own, established [financial] models. In some instances, the analysts described the protocols in the context of regulations about the types of information that could be used, “We have important Chinese walls to ensure independence between our research and trading arms” (Participant 20) and “there are a lot of Chinese walls[15] between the research hub of the sell-side brokerage and investment banking or client coverage…we really don't very frequently share information.” (Participant 19).

Bennett, Sias and Starks (2003) show that investment philosophies are similar within each category of institutional investor. The findings of this study show that the institutional guidelines available to analysts appeared to be influenced by the investment strategy and focus of the analysts’ employer. For example, Participant 4 explained, “we’ve got a strong quality focus…that’s the type of investment process we have”. After referring to “*our* research processes” (emphasis added), Participant 10 explained the flexibility that each analyst has, “different [analysts] have different interpretations of what quality is. So it has to be very specific to what we do.” It was essential that the researcher considered the impact of company protocols on analysts’ decision-making so that their behaviours are not misconstrued to be irrational e.g. what could be perceived as “herding” of analysts within the same organisation could be merely compliance with company guidelines and investment philosophy.

4.2.11. Interaction between buy side and sell-side researchers

As explained in Chapter 3, some of the participants in this study had worked as sell-side researchers in the recent past and were working as buy-side analysts at the time of the interview. These participants provided insight into the dynamics of the relationship between buy and sell-side researchers and how the buy-side analysts used research from the sell-side to make investment decisions.

The potential short termism from sell-side analysts became apparent as the now buy-side researchers reflected on their previous roles as sell-side analysts. Participant 4 explained:

[15] The term “Chinese Walls” is frequently used in academic and other publications that focus on the Global Analyst Settlement Agreement of 2003. This agreement between the Securities Exchange Commission and ten major investment banks, stipulated that the research and investment banking arms are to be kept separate.

When I contrast my work as a sell-side [analyst] versus now, there's a lot of overlapping in analysing companies analysing financials, analysing business strategy. But I would say … when you're on the sell-side, there's a lot of focus in short term metrics. There's six-month earnings, next year's earnings, sales of the last quarter, or whatever it may be.

- Participant 4

It also emerged that buy side researchers are well aware of the proclivity for bias from the sell-side researchers. This leads to scepticism on the part of the buy side analyst. For example, Participant 10 explained:

I'm now on the buy side - on the sell-side, you really do rely on management and being in management's good graces. So you try to toe the line as much as possible.

- Participant 10

This scepticism on the part of buy-side analysts is discussed in the context of the Indian market by Chaudhury *et al.* (2022). There are very few brokerage houses in India, and many are shareholders of the companies that are covered by the sell-side analysts. Furthermore, concerns about the structure of incentives for sell-side analysts also contribute to the scepticism of recommendations from sell-side analysts. These concerns are especially relevant considering the high level of judgement and understanding required when interpreting relatively complex financial items, such as intangibles (Chaudhury *et al.*, 2022).

The scepticism faced by sell-side researchers is much like the scepticism that they have when dealing with company reports or in discussions with management. The role of the sell-side analysts as "information intermediaries" (Hansen, 2015 p.61) was highlighted – they use information from companies and provide information to institutional investors and the rest of the market.

Interestingly, Participant 20 contended that buy-side researchers have a "pre-formed view" of a company for investment purposes and they will favour sell-side research that supports their view. This observation suggests the potential for confirmation bias on the part of the buy side analysts as consumers of information and further highlights the role of sell-side analysts as information intermediaries.

4.2.12. Difficulties in the sell-side equity research industry

During the interviews, participants discussed the difficulties that they faced as sell-side analysts. These challenges have been covered in the discussions in prior sections of the present chapter. However, the challenge of a lack of activity in certain sections of the JSE has not been specifically discussed as it was not a theme that was prominent in prior research regarding sell-side analysts.

Liquidity and participation were raised as issues specifically for JSE -listed companies. These weaknesses made it difficult for analysts to collate and track reliable and informative price data for smaller companies. Coverage of smaller, lesser-known companies had been identified as an opportunity for analysts. Participant 7 explained, ,"the less covered [the company] is, the better the opportunity" but that "it's becoming harder, particularly for smaller South African corporates, to get [reliable price data]".

Studies on liquidity on the JSE are well established in the literature (for example, see Paige, Britten and Auret, 2013). Most relevant for the context of difficulties faced by sell-side analysts, is research on liquidity and market efficiency. Liquidity of equity markets is affected by exogenous transaction costs, private information about share fundamentals and the structure of the exchange on which the share is listed (Young & Auret, 2018). Young and Auret (2018) evaluated liquidity in the context of trading platform upgrades and the establishment of a colocation facility for JSE traders, all of which enabled faster and more responsive trading on the JSE. However, it was noted that higher volatility in trading volumes could have been a result of the increasing uncertainty relating to the South African market for the period under analysis[16]. It was therefore difficult to isolate liquidity changes due to the technological and structural changes in the JSE from those caused by macro-economic factors and general investor confidence. The results of the study showed that predictability of returns decreased over the sample period although the index was found to be less informationally efficient over the same period. They found that although the structural changes in the JSE enabled easier algorithmic trading, algorithmic traders are unlikely to have transacted on information about company fundamentals. As a result, their trades do not necessarily result in a greater degree of informational efficiency on the JSE. Amongst others, the authors also cite the "emerging market status of South Africa and its susceptibility to the exogenous shocks and contagion effects that plague developing countries during periods of uncertainty" (Young & Auret, 2018 p.220) as reasons for the lack of predictability of returns on the JSE. On a similar note, Participant 12 discussed the emerging market status of the JSE – "If there's a shake-up in some of the bigger markets, and you need to find margin, you basically find margin by reducing your SA trade." Participant 14 also cited "global risk on, risk off sentiment" as a driver of returns on the JSE.

Participant 12 cited fewer analysts who contribute to the broker consensus that is published on financial research databases such as Bloomberg. As an example, the participant proffered the example of a financial institution that had recently reduced its complement of sell-side researchers who cover South African companies. Financial institutions were reluctant to spend significant amounts of money on sell-side research, preferring instead to "build their own in-house research capabilities." They therefore ended up "paying the street[17] less".

This issue has recently been highlighted by Hettler, Skomra and Forst (2023) in research titled, "The great sell-side sell off: evidence of declining financial analyst coverage", which, according to the authors, is the first to examine the decline in analyst coverage over the past decade. The study found that the number of analysts following firms declined by 17.8% globally between 2011 and 2021, with the decline being most pronounced in small-cap firms. This reduction in following has resulted in a decrease in analyst forecast accuracy, particularly for non-developed markets. The declining demand for sell-side research is attributed to a global shift to passive investments due to their cost efficiency as well as key regulatory changes.

The mixed method design of this study allowed the researcher to evaluate the theme of declining analyst coverage using the quantitative data gathered for this study. Descriptive statistics showing trends of analyst coverage in the sample are presented in Table 11.

[16] 2012 - 2015
[17] Sell-side researchers

Table 11: Trends of analyst coverage in the sample[18]

Year	2016	2017	2018	2019	2020	2021
Number of analysts	148	154	170	175	137	130
Number of asset management firms	51	52	45	51	46	42

The data affirms the theme of a declining number of analysts that cover JSE-listed firms. Although the number of analysts increased from 2016 to 2018, there has been a decline to 2021. The number of asset management firms in the sample shows a 17.65% decline from 51 asset managers in 2016 to 42 asset managers in 2021[19].

As detailed in the literature review, research houses have responded to the issue of lack of sell-side coverage. The academic work on sponsored research focuses on markets outside of South Africa. Anecdotal evidence on sponsored research is provided in a special report by Anthony (2022) in a special issue of the Financial Mail. In the report, the head of equity research at a large financial institution (at the time of writing) explained that his employer has a corporate-commissioned research offering whereby many small and midcap shares that are not covered by the broker community due to regulatory changes, pay for research so that consensus forecasts can be generated. This offering contributes to liquidity in the share and its investment case is better understood by investors.

In the Literature review section of this report, the researcher explained that certain research companies and brokerage firms offer company sponsored research. Blue Gem Research is a notable example as it offers *only* commissioned research (Blue Gem Research, 2013). Chronux Research is another research house that is “the leading Corporate Sponsored Research house in South Africa” (Chronux, 2023). However, research reports from the latter were not available on the company’s website. Merchantec offers corporate finance advisory and equity research services (Merchantec Capital, 2023). Edison Research is a London-based research firm that covers 225 companies globally (Edison Group, 2023). The results of a cursory analysis of commissioned research reports from a sample of research firms are summarised in Table 12 and detailed below. To eliminate selection bias, the researcher chose the most recent research reports at the time of writing.

[18] This table contains of the number of analysts and asset managers to illustrate a reduction in recommendations and asset managers for the period from 2016 to 2021. Details of the total number of analysts, recommendations and asset managers for the entire period is provided in the section on “Quantitative Data” of this report.
[19] Although the sample of recommendations extended to 2022, the data represents only part of the year and has therefore been excluded from the trend analysis.

Table 12: Summary of commissioned research reports

Research Company: Blue Gem Research					
Subject Company	**Market Cap.**	**Report Date**	**Report Title**	**Implied Return (12 month)**	**Disclosed Conflicts of Interest**
Metrofile Holdings	R1.3bn	26 Sep 23	FY 23 Results – Great Top-line Growth	65%	A and B
Sabvest Capital	R2.8bn	28 Aug 23	Growth Despite Tougher Period	73%	B and C
Astoria Investments	R604m	21 Aug 23	Durable Performance & Cautionary Issued	33%	B
Research Company: Merchantec Capital					
Subject Company	**Market Cap.**	**Report Date**	**Report Title**	**Implied Return (12 month)**	**Disclosed Conflicts of Interest**
Libstar Holdings	R2.2bn	19 Sep 23	Interim Results Equity Update	No target price disclosed	A
AVI	R25.1bn	13 Sep 23	Full Year Results Equity Update	No target price disclosed	A
RCL Foods	R8.9bn	08 Sep 23	Full Year Results Equity Update	No target price disclosed	A
Research Company: Edison Research					
Subject Company	**Market Cap.**	**Report Date**	**Report Title**	**Implied Return (12 month)**	**Disclosed Conflicts of Interest**
Datatec	R8.6bn	5 Jun 23	On a growth track for FY24	98%	A and B
Datatec	R7.92bn	5 Oct 23	Sustained demand in H124	No target price disclosed	A and B
Datatec	R8bn	23 May 23	Starting FY24 in a strong position	No target price disclosed	A and B
Pan African Resources	GBP436m	07 Jul 22	Building steam	22%	A and B

Legend - Conflicts of interest: A. Research is commissioned; B. Analyst holds long or short personal positions in the company; C. Analyst is an officer, board member or director of the company.

The market capitalisation of companies covered ranged from R25.1bn (AVI) to R604m (Astoria Investments). This suggests that coverage is not limited to smaller firms with thin analyst coverage. For example, AVI was followed by between eight and ten analysts for the period of analysis in the quantitative analysis contained in this study.

As with traditional sell-side research reports, the commissioned research reports (or "Results notes") are typically released shortly after the release of the JSE SENS trading updates. These Results Notes include a summary of the companies' most recent results and their growth prospects, with firm and industry-specific drivers thereof. The focus of the reports are the valuations, which are calculated using a discounted cash flow or P/E multiple. Reports appear to be optimistic about the companies' prospects, with most forecasting positive returns. Further analysis with the required rigour of an academic study is deferred to further research.

In the section on "Use of integrated reports", the researcher identified the reliance by analysts on company management for information about the future prospects of the company. The emergence of sponsored research is a response to declining analyst coverage of small to mid-cap firms, where independent coverage was not considered economically viable. The commissioning of research by companies may further hinder an objective review of the company and possibly lead to overly optimistic forecasts in relation to the company.

4.3. Results: Quantitative Data Analysis

4.3.1. Descriptive statistics

As in Barth *et al.* (2017), this research uses the integrated report quality scores for the year prior to the analysts' recommendations. In other words, analysts' recommendations in say, 2016 (t0) were modelled as a function of integrated report quality scores in 2017 (t1). Barth *et al.* (2017) searched JSE SENS announcements to determine the dates on which the integrated reports are released to the public. Where they were unable to find the exact dates on which the reports were released, the authors used the release date of the annual reports. In these instances, recommendations issued by analysts after the release of the annual reports (and by implication, not the integrated report) were modelled as a function of integrated report quality scores. There is a notable limitation to this type of analysis. It makes the tacit assumption that the information in the report was in fact used in the formulation of the recommendation. In research that seeks to evaluate consequences of information quality, it is imperative that the report which was actually used by the analyst is considered. It is therefore critical that the exact date of the release of the integrated report is determined prior to conducting statistical analysis.

In this research, we found that it is the exception that an exact date of release of integrated reports is not available. This was done through an analysis of SENS announcements as in Barth *et al.* (2017) for the 67 companies included in the present research. SENS announcements were located on the company websites and/ or financial databases. The researcher found that it was the norm for companies to release abridged results a few weeks before the integrated reports are published on the companies' websites and sent to shareholders. This is in accordance with the Companies Act requirement that listed companies are required to publish results twice a year, within three months of mid-year and year-end. During the analysis of SENS announcements, the researcher was able to find the exact date of release of the integrated report for all but ten companies out of the 67 included in the analysis. Notably, we found that there were 39 days, on average, between the release of the annual report and the integrated report.

It follows that the assumption that the integrated report release date and the annual report release date are the same is unlikely to hold for the majority of companies on the JSE. Typically, a “No change” SENS announcement is made on the date of release of integrated reports to confirm that the results contained in the Integrated Report are the same as those that were released in the abridged results. In the time period before the release of the integrated reports, many analysts release their investment recommendations based on the abridged results. Figure 16 shows the number of recommendations released by analysts per day, post the release of the annual results. The analysis in this research showed that 269 recommendations were released on the date of the release of annual results and 222 recommendations were released on the day after these results were released. In comparison, Figure 17 shows the number of recommendations released by analysts, post the release of the integrated report. It shows that 63 recommendations were released on the date of publication of the integrated report and 66 recommendations were released the day after the report was published.

Figure 16: Trend of recommendation releases post release of annual financial results

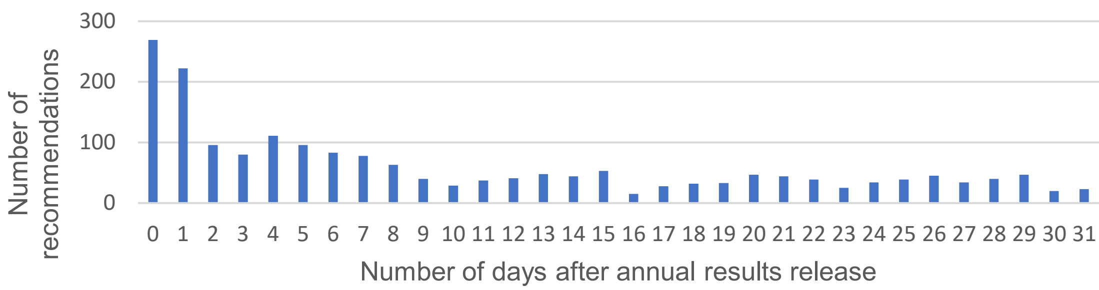
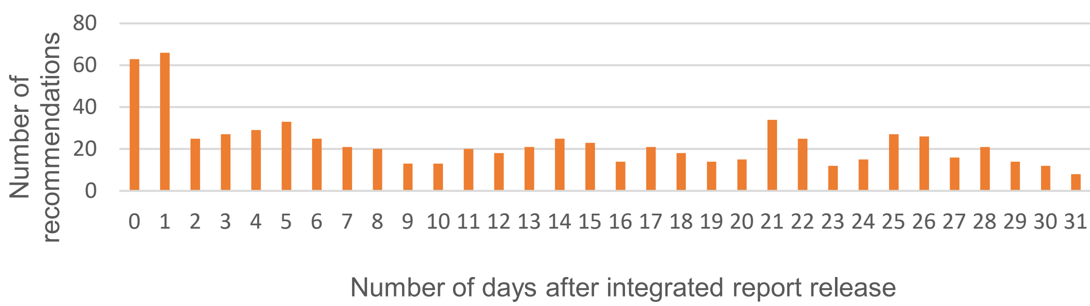


Figure 17: Trend of recommendation releases post release of integrated report results



It is apparent from this empirical analysis that analysts’ recommendations are based mostly on the annual financial results instead of the integrated report (269 recommendations issued immediately after the annual report compared to 63 recommendations issued immediately after the integrated report). Given the findings of the lack of noticeable market reaction by Willows and Rockey (2018), our initial evidence shows that analysts follow the same pattern of reaction as the rest of the market. It is therefore unsurprising that studies that examine analyst reaction to company financial information, use the release date of earnings announcements as the event date (Bessiere & Elkemali, 2014). Furthermore, our descriptive analysis may indicate that the integrated reports are mainly used to confirm the recommendations based on the annual results. A more rigorous event study for the period under analysis is deferred to future research – in this research, we sought to test the hypotheses as defined in Section 1.5.

Further descriptive statistics relating to analysts are presented in Table 13, to provide further anecdotal evidence of the use of integrated reports. These statistics incorporated accuracy of forecasts, as they were calculated respectively for the most and least accurate analyst, on average, in the sample of data.

Table 13: Comparison of most and least accurate analyst

Characteristic	Most accurate	Least accurate
Experience	11 years (CFA)	10 years (CFA)
Number of recommendations issued in the quarter after the annual results are released (average)	1.12	1.0
Industry	Telecommunications	Consumer Goods
Total number of this analyst's recommendations included in analysis	18	5
Recommendations issued before integrated report release	17	4
Recommendations issued after integrated report release	1	1
Average time taken to release a recommendation (after annual results release)	23.72 days	11.8 days
Longest time taken to release a recommendation (after annual results release)	91 days in 2020	27 days in 2020

Source: Author’s own

The comparison shows a negligible difference in the number of years of experience, with both analysts having the same professional designation. Each analyst appears to issue their recommendations once per quarter in average, which coincides with the frequency of release of SENS announcements containing quarterly trading updates. Notably, neither analyst appears to wait for the integrated report to be released before issuing their recommendations. The single instance of the recommendation being issued after the integrated report was issued, was in 2020 and possibly the result of delays relating to the COVID-related lockdown. These statistics provide initial anecdotal evidence that the use of integrated reports does not improve forecast accuracy.

4.3.2. Results of the measurement model

The reliability of the measurement model was determined with reference to the factor loadings (Bollen & Noble, 2011), presented in Table 14.

Table 14: Measurement model results – initial

Variable	Indicator	Mean	SD	Factor loading
Integrated Report Quality	FC	0.525	0.191	0.966
Integrated Report Quality	CE	0.601	0.168	0.984
Integrated Report Quality	GP	0.583	0.583	0.991
Forecast Decision Quality	FERR	0.379	3.164	0.854
Forecast Decision Quality	FDIS	0.000369	n/a	0.662
Availability	AVL1	0.031	0.058	0.235
Availability	AVL2	0.165	54.81	0.933
Availability	AVL3	0.137	55.216	0.901
Overconfidence	OVC1	0.108	0.117	0.835
Overconfidence	OVC2	0.480	0.219	0.776
Overconfidence	OVC3	0.149	0.117	0.727
Overconfidence	OVC4	0.174	0.301	0.236
Loss Aversion	LAV1	1.331	1.301	0.770
Loss Aversion	LAV2	2.527	2.186	0.913
Herd Behaviour	HER1	0.287	6.391	0.914
Herd Behaviour	HER2	5.846	13.148	0.902
Share Price Performance	SPP	0.281	3.307	1
Profitability	PR	0.388	0.179	1
Size	SZ	19 645 0321	41 515 284	1
Experience	EXP	15.235	6.789	1

Bollen and Noble (2011) explain that factor loadings represent the relationship between the observed variable/ measurement indicators and the underlying latent variable. In other words, factor loadings show how much of the variance in an observed variable can be explained by a latent factor. Following an analysis of the Factor Loadings in Table 3, all indicators with a loading less than 0.6 were removed, in line with the guidance provided in Bollen and Noble (2011). In addition to the results shown in Table 14, a depiction of the initial measurement model from SmartPLS4 is provided in Appendix C.

In PLS SEM, factor loadings are not subjected to tests of statistical significance because the method is primarily predictive rather than confirmatory. PLS-SEM is focused more on maximising the explained variance of the dependent constructs and predicting outcomes. Therefore, statistical significance of individual loadings is not central to its purpose. Furthermore, in PLS-SEM, the focus is on assessing the reliability and validity of measurement models using indicators such as composite reliability, average variance extracted and discriminant validity (provided in Table 16 and Table 17). Therefore, there is no statistical significance associated with each factor.

Prior to analysing the results of the measurement and structural model, the researcher checked for outliers. Outliers are observations or data points which are noticeably different from the rest of the data points in the sample (Hair *et al.*, 2019). Aguinis, Gottfredson and Joo (2013) conducted a literature review to establish best practice in identifying and dealing with outliers in regressions and SEM analyses. Less than 5% of the 232 studies included in the study accounted for outliers in a SEM analysis. The researchers acknowledge that this may be due to the relatively lower number of studies that involve SEM instead of regressions. However, they also note that there are very few textbooks that include discussions of outliers in SEM compared to regression analyses. For structural equation models, Kline (2015) cautions that the existence of even very few outliers can distort the results and fit of the model. For structural equation models, outliers can be further described as:

i. Error outliers, which arise as a result of inaccuracies in collecting, preparing and computing data.
ii. Interesting outliers, which are non-error data points that contain valuable insights.
iii. Model fit outliers, which affect the fit of the model.

These description categories are not mutually exclusive. However, a key insight from Aquinis *et al.* (2013) is that outliers should be carefully analysed before they are discarded. The authors further present the variety of methods used in the literature to identify outliers in a SEM analysis. Specifically, generalized Cook's Distances was prominent as an indicator to identify outliers in SEM. Therefore, in this research Cook's Distances were calculated for the data in SPSS to identify outliers. The results are displayed graphically in Appendix E and Appendix F. The following observations were identified as outliers:

Table 15: Outlier observations

Observation Unique Identifier	Company and Year
AMS18	Anglo American Platinum (2018)
ANH17	Anheuser-Busch InBev (2017)
ANH18	Anheuser-Busch InBev (2018)
ANH19	Anheuser-Busch InBev (2019)
ANH20	Anheuser-Busch InBev (2020)
IMP19	Impala Platinum Holdings (2019)
NED16	Nedbank Group (2016)

All outliers were re-checked for errors in collection and calculation, especially since ANH appeared to be indicative of a systematic error. Further analysis was warranted, especially since Anheuser-Busch InBev was the involved in a business combination with SABMiller. The transaction was completed in October 2016 (ABI, 2016) The acquisition of SABMiller at GBP 68bn represented the fourth largest of any corporation at the time and was therefore a true "outlier" in that sense. Upon rechecking the data and calculations of data on Anheuser-Busch InBev, no errors were noted. The analysts forecast error (average of 11.09) and forecast dispersion (average of 20 990 across all years) for the company was significantly larger than the averages noted in Table 16 below. Furthermore, the number of recommendations issued for the company (26.5 on average) was also higher than the overall average of 7.36 recommendations per company year, indicating a highly followed company. This finding warranted further investigation that other companies with large analyst following were also flagged as outliers. However, this was not found to be the case and the researcher concluded that there were no errors that affected the rest of the sampled company years. A key advantage of the mixed-method approach employed in this study is that outliers or potential outliers can be further investigated using qualitative techniques (Aguinis *et al.*, 2013). The researcher therefore identified the analysts who made the recommendations relating to AnHeuser-Bush Inbev and approached them for an interview. This approach is consistent with this study's convergent design where qualitative results are used to confirm the quantitative results (Creswell & Creswell, 2017). Interview data is analysed and discussed in Section 4.2.

Finally, the model was re-run with and without the outliers and the model fit (SRMR) was assessed. However, no change was noted in the model fit. This study employs bootstrapping methods in partial least squares structural equation modelling, which does not assume that the data are distributed in any specific manner. The flexibility provided as part of this analysis provides results that are robust in the presence of outliers (Aguinis *et al.*, 2013). Therefore, all further results represent the model including the observations in Table 15.

According to Kline (2015), the validity of the measurement model must be assessed in terms of convergent and discriminant validity. Convergent validity refers to the extent to which indictors of a specific latent variable (or construct) share a common variance. Discriminant validity refers to the extent to which construct is distinct from other constructs in the model. To confirm the suitability of the revised measurement model, the Cronbach Alpha, Composite Reliability and Average Variance Extracted were calculated based on the remaining indicators. The results are summarised in Table 16, with an extract from SmartPLS 4 contained in Appendix C.

Table 16: Measurement model results after removal of indicators with low factor loadings

Variable	α	CR	AVE
Integrated Report Quality	0.980	0.987	0.962
Forecast Decision	0.687	0.853	0.746
Availability	0.869	0.938	0.883
Overconfidence	0.699	0.833	0.624
Loss Aversion	0.601	0.821	0.700
Herd behaviour	0.788	0.890	0.802

Construct reliability was confirmed by Cronbach's alpha values, composite reliability and factor loadings above 0.5 (Hair *et al.*, 2019). According to Kline (2015), the reliability coefficient that is most often reported in the literature is Cronbach's Alpha or coefficient alpha. This metric measures the internal consistency reliability, or the degree to which the indicators of a specific latent variable are consistent across each other. The conceptual equation is:

$$a_c = \frac{n_i \overline{r_{ij}}}{1 + (n_i - 1)\overline{r_{ij}}} \qquad \textit{Equation 34}$$

where n_i is the number of items and $\overline{r_{ij}}$ is the average Pearson correlation between all pairs of items.

Composite reliability (CR) and Average Variance Extracted (AVE) have been proposed by Raykov and Marcoulides (2004) as superior alternatives to the Cronbach's Alpha for models which use reflective measures (as in this study). CR is the ratio of explained variance to total variance. A higher CR value show that the indicators are measuring the latent construct reliably. Similarly, the average variance extracted (AVE) is the average of the squared standardised pattern coefficients for factors that depend on the same factor but are specified to measure no other factors (Kline, 2015). The measure provides an indication of how well the indicators that load onto a latent variable actually measure that variable. A higher AVE value indicates that a larger proportion of the variance in the observed variables is accounted for by the underlying latent construct, and therefore, better convergent validity (Kline, 2015).

For the data in this study, a high degree of reliability and validity is expected due to the nature of the scoring process followed by the expert adjudicators of the EY awards. As highlighted by Maroun (2019), the EY scoring criteria has been used repeatedly across various contexts, enhancing the reliability of the scores generated from the instrument. Convergent validity was assessed by examining the average variance extracted, with a minimum threshold of 0.4 (Fornell & Larcker, 1981).

Discriminant validity was tested using the Fornell-Larker Criterion. Discriminant validity refers to the extent to which a construct is distinct from other constructs – it captures phenomena not represented by other constructs in the model (Kline, 2015). According to the Fornell-Larcker Criterion, discriminant validity is established when the square root of the average variance extracted (AVE) for each construct is greater than the correlations between that construct and any other construct in the model. The criterion therefore considers constructs relative to each other. It checks whether a latent variable explains more variance in its associated indicators than it shares with other latent variables. This test therefore requires a comparison of the square root of the average variance extracted of each construct to be larger than the correlations between the construct and any other construct in the analysis. Results are presented in Table 17.

Table 17: Fornell-Larker Criterion

	AVL	EXP	FCD	HRD	IRQ	LAV	OVC	PRF	SPP	SZ	UPER
AVL	**0.939**										
EXP	0.406	**1.000**									
FCD	0.538	0.183	**0.863**								
HRD	-0.036	-0.047	-0.080	**0.896**							
IRQ	0.017	0.050	-0.007	0.024	**0.981**						
LAV	-0.141	-0.097	-0.154	0.281	-0.170	**0.837**					
OVC	0.837	0.362	0.567	0.033	0.044	-0.149	**0.789**				
PRF	-0.022	0.004	0.003	0.065	-0.049	0.006	0.033	**1.000**			
SPP	-0.079	-0.008	-0.045	-0.054	-0.117	0.002	-0.045	0.034	**1.000**		
SZ	-0.040	0.000	-0.010	0.066	-0.066	0.007	-0.018	0.945	0.021	**1.000**	
UPER	-0.042	-0.051	0.054	0.029	-0.123	0.152	-0.140	0.067	-0.013	0.052	**1.000**

In the results presented in Table 17, the diagonal values represent the square root of the AVE for each construct, not the correlations themselves. Since AVE is typically less than 1 (because it reflects the proportion of variance captured by the construct, excluding measurement error), the diagonal values are also expected to be less than 1. In the table, the numbers in bold in the diagonal, are the square root of the average variance extracted. The rest of the numbers in each column represent the correlation between the construct in the column heading and the rest of the variables in the model. In Table 17, the square root of the AVE for each variable is greater than its correlations with the other variables. These results indicate a low degree of shared variance between the latent variables in the model. Specifically, each variable is discriminant and does not measure the same construct as other variables in the model.

A summary of the reliability and validity assessment criteria that were applied to the measurement model is presented in Table 18.

Table 18: Summary of measurement model assessment criteria

Criteria	Indicator	Criteria	Source	Application to measurement model
Reliability of measurement of constructs	Cronbach's alpha (α) Composite reliability (CR)	α > 0.5 or 0.7 CR > 0.5 or 0.7	Hair *et al.* (2019)	Lowest Cronbach Alpha recorded was 0.601 and lowest CR recorded was 0.702.
Convergent validity	Factor loadings Average Variance Extracted	Loading > 0.5 AVE > 0.4 or 0.5	Hair *et al.* (2019)	All indicators with a factor loading of less than 0.7 were removed from the measurement model.
Discriminant validity	Fornell-Larcker	√ AVE > Correlations between constructs	Fornell and Larcker (1981)	No correlations between constructs were detected.

Source: Adapted to current model from Pamacheche (2020)

4.3.3. Results of the structural model

The structural model was used to test each of the following hypotheses, developed from the review of prior literature.

H1: The quality of equity analysts' forecasts improves with an increase in the quality of information in the integrated reports.

H1.a. The quality of information contained in a company's integrated reports has a positive relationship with the quality of analysts' forecasts for that company.

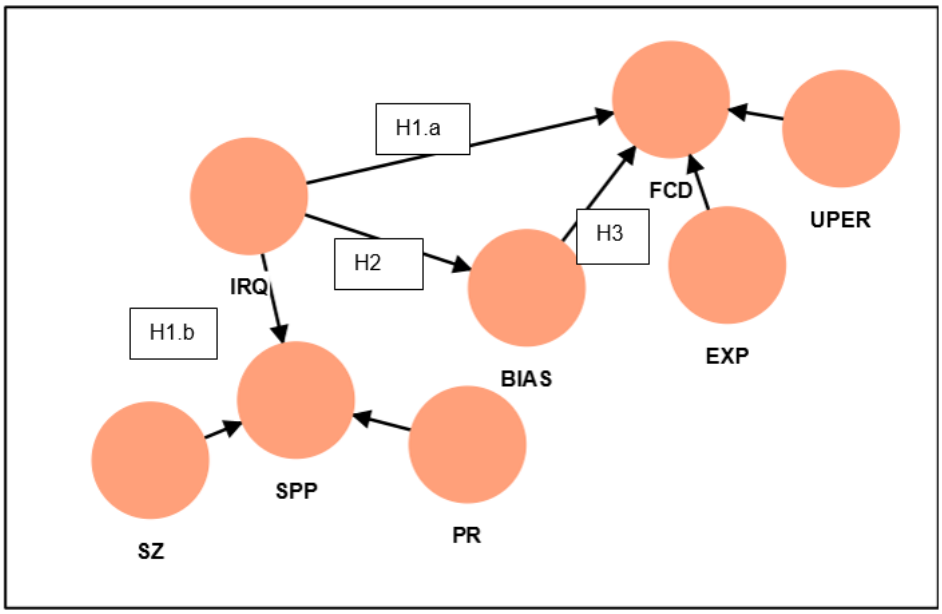
H1.b. The quality of information in a company's integrated reports has a positive relationship with share price performance of that company.

H2: Poor quality integrated reports increase analysts' proclivity to behavioural bias.

H3. The behavioural bias of equity analysts has an effect on the quality of their forecast decisions.

These hypotheses were tested in the structural model as depicted in Figure 13 (reproduced in this section for ease of reference).

Figure 13: Structural Model 2 (SM2)



The structural model was evaluated by examining the path coefficients and their corresponding statistical significance. The path coefficients and their degree of significance were calculated using a boot-strapping procedure in SmartPLS4. The results of the structural model are set out in Table 19.

Table 19: Regression Coefficients of the Structural Model

Dependent variable: FCD		
	Path Coefficient	T-statistic
IRQ	-0.004	0.964
AVL	0.633	2.411**
OVC	0.313	0.514
LAV	0.008	2.241**
HER	-0.056	0.177*
UPER	0.086	1.625*

EXP	0.432	0.667
Dependent variable: SPP		
	Path Coefficient	T-statistic
IRQ	-0.108	1.163
PRF	0.211	0.061
SZ	0.026	0.090
Dependent variable: AVL		
IRQ	0.010	2.495**
Dependent variable: OVC		
IRQ	0.026	1.654*
Dependent variable: HER		
IRQ	0.040	0.937
Dependent variable: LAV		
IRQ	-0.202	0.326

Note: (*) Indicates statistical significance at the 10% level; (**) Indicates statistical significance at the 5% level; (***) Indicates statistical significance at the 1% level.

The model fit criteria from Kline (2015) was met as a Standardised Root Mean Square Residual (SRMR) of 0.07 was recorded, which is less than the suggested 0.08, indicating acceptable model fit (Hu & Bentler, 1999).

For share price performance (SPP), an R-squared of 0.057 was recorded. None of the independent variables (IRQ, PRF and SZ) were found to exhibit significant effects.

The insignificant relationship between IRQ and FCD (t-stat = 0.0964) is not unexpected, given the results of the analysis of descriptive statistics that showed a muted response to IRQ by the analysts. For Forecast Decision Quality (FCD), an R squared of 0.834 was recorded. Despite this relatively high R-squared, the relationship between Integrated Report Quality (IRQ) and FCD was negative and insignificant. The biases of availability, loss aversion and herding were found to have a significant relationship with FCD. Availability (AVL) was found to have a strong, positive and significant effect on FCD, indicating that greater availability bias can lead to an increase in forecast dispersion. Loss Aversion (LAV) was also shown to have a positive and significant effect on FCD.

In the context of structural equation modelling, endogeneity refers to the situation where the structural error associated with a dependent latent variable is correlated with one or more of the latent variables that are pointing to that dependent variable. It can arise due to simultaneous causality and common method errors (Hult *et al.*, 2018). However, it appears that addressing the issue of endogeneity is a relatively under-developed area of research for partial least squares structural equation models. In a review of articles published in high-ranking marketing journals over a ten- year period from 2008 to 2017, Hult *et al.* (2018) found that none of the 43 articles tested for endogeneity. We find similar evidence in the articles which use SEM in finance or accounting research. Barranhof *et al.* (2007) do not mention the potential impact of endogeneity on their results. Although the relationship between bias and the investment decision is commonly evaluated using SEM, considerations of the potential impact of endogeneity appears to be lacking, even from more recent research endeavours (Ahmed, Riaz, Aqdas, Ul Hassan, 2021). By contrast, Ittner *et al.* (1997) acknowledge the potential for the independent variables in their structural model to be endogenous choice variables. They also explain the implications of such an issue, i.e. that the estimates for the structural coefficients could be inconsistent. They call for future, more sophisticated analyses which incorporates suitable exogenous instrumental variables.

There are diverse views on the impact of endogeneity in a structural equation model. These views vary depending on whether the model is used for predictive or explanatory purposes. The purpose of a predictive model is to predict case values of the dependent variables whilst the purpose of an explanatory model is to interpret the structural paths. Barth *et al.* (2017) applied this line of reasoning to evaluate the impact of endogeneity on the results of their regression model. They contended that their tests were of associations; they were not intended to draw causal inferences. Yet, in a review of the literature on corporate disclosure, Healy and Palepu (2001) bemoan the limitations placed on interpretations of findings of many of the studies in the review. These limitations, the authors contend, arise from significant endogeneity problems. With such limitations on inference probably in mind, Barth *et al.* (2017) included a discussion of the potential effects of endogeneity on their analysis.

Endogeneity can also arise when omitted variables correlate with one or more independent variables and the dependent variable. In this research, we have therefore undertaken a thorough search of the literature to identify variables, control variables and relationships. In addition, the use of qualitative data from the interviews with analysts provides additional insights on whether specific variables have been omitted. For this reason, the interviews took a semi-structured format and coding was a mixture of deductive and inductive methods, allowing themes to emerge.

However, Ebbes, Papies and van Heerde (2017) caution that endogeneity can arise despite the thorough selection of control variables. It is therefore recommended that statistical approaches are employed to detect and address endogeneity. These approaches can be broadly categorised as methods that include instrumental variables and those that do not. For this research, the Gaussian copula method was chosen because of the challenge associated with the identification of conceptually fitting instrumental variables (Eckert & Hohberger, 2022). Having determined that the latent variables were non-normally distributed, the Gaussian copula is calculated as per Ebbes *et al.* (2017):

$$c^* = \Phi^{-1}[H(X_1)] \qquad \textit{Equation 35}$$

where H (x) is the empirical cumulative density function and Φ^{-1} is the inverse normal cumulative density function.

In SmartPLS4, the statistical software of choice for this project, the Gaussian copula control function can account for several potentially endogenous regressors in the model. This is achieved through the inclusion of multiple copula terms. Specifically, the researcher used the PLS-SEM algorithm to estimate the model including Gaussian copula terms and their significance was determined using bootstrapping. A significant copula coefficient indicates an endogeneity issue with the dependent variable. However, the endogeneity is treated by included the copula in the model (Park & Gupta, 2012; Hult *et al*., 2018). For this study, the researcher tested for endogeneity using Gaussian copulas in SmartPLS4. The results showed an endogeneity issue with the availability bias latent variable. Therefore, we include the availability copula in the structural model results in Table 20 below. All other results remain unchanged.

Table 20: Revised Results of the Structural Model with Gaussian Copula

Dependent variable: FCD		
	Path Coefficient	T-statistic
IRQ	-0.004	0.964
AVL	0.633	2.411**
GC(AVL)	0.633	2.347**
OVC	0.313	0.514
LAV	0.008	2.241**
HER	-0.056	0.177
UPER	0.086	1.625
EXP	0.432	0.667
Dependent variable: SPP		
	Path Coefficient	T-statistic
IRQ	-0.108	1.163
PRF	0.211	0.061
SZ	0.026	0.090
Dependent variable: AVL		
IRQ	0.010	2.495**
Dependent variable: OVC		
IRQ	0.026	1.654*
Dependent variable: HER		
IRQ	0.040	0.937
Dependent variable: LAV		
IRQ	-0.202	0.326

Note: (*) Indicates statistical significance at the 10% level; (**) Indicates statistical significance at the 5% level; (***) Indicates statistical significance at the 1% level.

We interpret the empirical results relating to availability cautiously. Fortunately, the mixed methods design of this study allowed the researcher to incorporate insights on the availability bias from the qualitative interview process, thereby contributing to the reliability of the final results. As a final measure, we exclude availability from the regression model discussed in the following sections of this study.

4.3.3.1. Additional analysis: Regression model

As an additional consideration of robustness and for comparison, the researcher also used a regression model to further analyse the data. Our additional analysis using a regression model is appropriate because both SEM and regressions use the same mathematical foundation, in that SEM comprises the simultaneous estimation of several independent regression equations (Hair *et al.*, 2019). The choice between SEM and regression analysis is therefore highly dependent on the data available (Bollen & Noble, 2011; Kline, 2015). Nevertheless, our use of a regression model came at the cost of the benefits of SEM over multiple regression, since a construct can act as a dependent variable in one path (or relationship) and an independent variable in another path (or relationship) (Hair *et al.*, 2019). This meant that a regression model, could not be used to test the second hypothesis, as the bias variables were used as dependent variables in the testing of the first hypothesis. In addition, while the latent variable modelling allowed for the use of multiple indicators for each latent variable, the inability of regression models to handle latent constructs meant that only one indicator variable had to be chosen as a measurement approximation for each variable in the regression model. A detailed discussion of the differences between a regression model and a structural equation model is contained in Sections 2.14.2 and 3.4.2. of this study.

The regression was performed in SmartPLS4, which is the same software that was used for the structural equation model in this study. This software is capable of producing reliable results for regressions. For data to be suitable for use in regression analysis, it must meet certain criteria, one of which is normality (Kline, 2015). The data in this study was known to be non-normal (see Section 3.5.2.). As such, the researcher used the natural logarithm of the data used in the structural equation model (Curran-Everett, 2018).

The following equation therefore applies, with a single dependent variable representing the quality of analysts' forecasts. As specified in Equation 24, FERR is measured as the *inverse* of forecast error, and is thus a measure of forecast accuracy.

$$FERR_{it} = \alpha + \gamma_1 FC_{it} + \gamma_2 LAV_{it} + \gamma_4 HER_{it} + \gamma_5 OVC_{it} + \gamma_5 UPERR_{it} + \gamma_6 EXP_{it} + \varepsilon_{it}$$

Equation 36

and:

$$SPP_{it} = \alpha + \gamma_1 FC_{it} + \gamma_2 PR_{it} + \gamma_3 SZ_{it} + \varepsilon_{it}$$

Equation 37

The results are presented in Table 22, alongside those of the structural model for comparison. A path diagram from the regression in SmartPLS4 is depicted in Appendix G.

Table 21: Regression Model Results

Dependent variable: FERR			
	Coefficient	**t-statistic**	**VIF**
FC	-0.046	0.808	1.034
OVC2	0.061	1.068	1.034
HER1	-0.154	2.720***	1.025
LAV2	0.044	0.758	1.066
UPER	0.175	3.054***	1.050
EXP	0.153	2.673***	1.039
Intercept	0.000	1.775**	
Adjusted R-squared	0.069		
Dependent variable: SPP			

	Coefficient	t-statistic	VIF
SZ	0.081	0.462	2.290
PRF	0.116	0.656	2.278
FC	-0.121	2.088**	1.004
Intercept	0.000	2.923	
Adjusted R-squared	0.017		

Note: (*) Indicates statistical significance at the 10% level; (**) Indicates statistical significance at the 5% level; (***) Indicates statistical significance at the 1% level.

It must be noted that no latent constructs were included in the regression, due to the method's inherent limitation to model latent variables (with multiple indicators). The implication for the regression model is that latent variables from the structural model had to be represented by only one measurement approximation. For example, the latent variable of FCD or forecast decision, is represented by a single measurement approximation, in this case, FERR (measure of forecast accuracy) and excludes FDIS (measure of forecast dispersion amongst analysts). A comparison of the results of the different forms of analyses is contained in subsequent sections of this report. This means that the two sets of quantitative analyses were performed using different measurement approximations for each variable (and therefore, for each bias). The analysis therefore reveals the extent of robustness of our results to changes in measurement approximations.

The results of the regression model and structural equation model are compared in Table 19 and discussed with reference to relevant qualitative findings in the Section 4.4: Synthesis of results – QUAL and QUAN.

4.3.3.2. Comparison of results – structural equation model and regression model

Table 22: Comparison of results from different quantitative methods

Hypothesis	Structural Model Result	Regression Result
H1. a. The quality of information contained in a company's integrated reports has a positive relationship with the quality of analysts' forecasts for that company.	Negative, Insignificant	Negative, Insignificant
H1.b. The quality of information in a company's integrated reports has a positive relationship with share price performance of that company.	Negative, Insignificant	Negative, Significant
H2.a: Poor quality integrated reports increase analysts' proclivity to heuristics and bias (Availability)	Positive, Significant	N/A
H2.b: Poor quality integrated reports increase analysts' proclivity to heuristics and bias (Overconfidence)	Positive, Significant	N/A
H2.c: Poor quality integrated reports increase	Negative,	N/A

Hypothesis	Structural Model Result	Regression Result
analysts' proclivity to heuristics and bias (Loss Aversion)	Insignificant	
H2.d: Poor quality integrated reports increase analysts' proclivity to heuristics and bias (Herding)	Positive, Insignificant	N/A
H3.a. The bias of equity analysts has an effect on the quality of their forecast decisions (Availability)	Positive, Significant	N/A
H3.b. The bias of equity analysts has an effect on the quality of their forecast decisions (Overconfidence)	Positive, Insignificant	Positive, Insignificant
H3.c. The bias of equity analysts has an effect on the quality of their forecast decisions (Loss Aversion)	Positive, Significant	Positive, Insignificant
H3.d. The bias of equity analysts has an effect on the quality of their forecast decisions (Herding)	Negative, Insignificant	Negative, Significant
Control: Upward Error	Positive, Insignificant	Positive, Significant
Control: Experience	Positive, Insignificant	Positive, Significant

Whilst the directional results were the same across both types of quantitative analyses, the levels of significance differed. Our conclusion is therefore made with consideration also of the qualitative analysis.

4.4. Synthesis of results – QUAL and QUAN

In the convergent design, qualitative and quantitative data are analysed separately, and the findings of the separate analyses are merged. This process facilitates the development of a comprehensive understanding of the results and enables meaningful inferences (Creswell & Plano-Clark, 2018). As suggested by Creswell and Plano-Clark (2018), the results from the qualitative and quantitative analyses are compared side-by-side in a joint display (see Table 23: Joint display of results).

Table 23: Joint display of results

Research Question / Relationship	QUAL Result	QUAN Result	Mixed methods comparison
H1. a. IR Quality and Forecast quality	Frequency, Historical Focus: Participant 8: [It] goes back to the motivation	Negative, Insignificant	Congruent

Research Question / Relationship	QUAL Result	QUAN Result	Mixed methods comparison
	that we're paid to put out information frequently. Impression management: Participant 8: you know the integrated report is information that the company wants to show you. But if there's something that's not great, they will gloss over it. Complexity: Participant 12, (Chartered Accountant): perhaps the accounting is getting too complicated… Direct interactions with management: Participant 8: I personally will only recommend the stock if I've met management. It goes back to the thing that I mentioned earlier - that trust element.		
H1.b. IR Quality and Share price performance	A qualitative view of the market perception of integrated reports cannot be provided as only analysts were interviewed, and they have direct access to management, unlike other investors.	Negative, Insignificant	N/A
H2.a: IR Quality and Availability	Ease of recollection of audit failures: Analysts who covered companies in which audit	Positive, Significant	Discrepant The quantitative findings indicate

Research Question / Relationship	QUAL Result	QUAN Result	Mixed methods comparison
	failures occurred were more alert to the possibility of misstatement. Participant 4 (covered a company involved in audit failure): “I have always been sceptical about the auditor’s tests” versus Participant 3 (had not covered a company involved in audit failure/ financial misstatements): auditors can’t detect fraud in all instances – you shouldn’t adjust companies that were not affected – that’s when you’re being biased. <u>Prioritisation of most recent information:</u> Participant 9: we live in an environment that is rapidly or constantly changing. Immediately. You put your model down, there's new information coming through, or that's developing in the market that actually will render your model completely out.		that better quality integrated reports are associated with greater availability bias.
H2.b: IR Quality and Overconfidence	<u>Reliance on the integrated report to make contrarian recommendations by ignoring the consensus.</u> Participant 4: I usually do all my analysis, and only afterwards would I look, once I've published my note to see what the market is thinking. And the reason was I didn't want to	Positive, Significant	Congruent

Research Question / Relationship	QUAL Result	QUAN Result	Mixed methods comparison
	be influenced by the other brokers and I didn't want to model to a number if that makes sense? Because then how honest are you really being with yourself? Then you've got zero differentiation.		
H2.c: IR Quality and Loss Aversion	Reluctance to produce downward revisions. Participant 2:You revise upwards more than you do downwards. The stock would have to move very, very highly against the house view for it to become a sell.	Negative, Insignificant	Congruent
H2.d: IR Quality and Herding	View of consensus forecast as a key source of information: Participant 3: I use the broker consensus to try and see if I'm not going haywire or if there's something else that is happening that I don't know about.	Positive, Insignificant	Discrepant Clustering around the consensus should reduce forecast quality.
H3.a. Availability and Forecast Quality	Prioritisation of most recent information: Participant 9: we live in an environment that is rapidly or constantly changing. Immediately. You put your model down, there's new information coming through, or that's developing in the market that actually will render your model completely out.	Positive, Significant	Congruent
H3.b. Overconfidence and Forecast	Frequency: Participant 8: [It] goes back to the motivation that we're	Positive, Insignificant	Congruent Measurement

Research Question / Relationship	**QUAL Result**	**QUAN Result**	**Mixed methods comparison**
Quality	paid to put out information frequently.		indicators for overconfidence include extent of deviation from consensus and frequency of release of forecast. Analysts who revise their forecasts frequently provide better quality forecasts.
H3.c. Loss Aversion and Forecast Quality	<u>Reluctance towards downward revisions:</u> Participant 4: It's easier for it to move into buy territory than it is to move into sell. You'd rather place a hold recommendation or even a neutral recommendation before you go down to sell.	Positive, Significant	Discrepant Reluctance to revise downwards, despite supporting data, should result in poorer quality forecasts.
H3.d. Herding and Forecast Quality	<u>Use of the broker consensus as a benchmark</u> Participant 10: [The broker consensus] is something that I can constantly benchmark myself against. Like where is the target price, you know, and then you go back into your model and then try to tweak the growth rate and tweak this and tweak this just so you get as close as possible to where the rest of the group is.	Negative, Insignificant	Congruent
Control: Upward Error and Forecast Quality	<u>Incentive to produce positive forecasts.</u> Participant 10: …you really do rely on management	Positive, Insignificant	Discrepant Exogenous incentives to

Research Question / Relationship	QUAL Result	QUAN Result	Mixed methods comparison
	and being in management's good graces. So you try to toe the line as much as possible.		produce positive recommendations, without regard to relevant information, should result in poorer quality forecasts.
Control: Experience and Forecast Quality	<u>Importance of experience:</u> Participant 20: One of our best analysts, ****, contributed a lot to the win because he has excellent industry and sector knowledge	Positive, Insignificant	Congruent

Our first research objective was to evaluate the association between integrated report quality and the information environment. Perhaps the most unequivocal finding in this study, across all methods of analysis, is the lack of relevance of the quality of integrated reports to the decision-making processes of analysts. Our descriptive statistics, in line with prior research (Rensburg & Botha, 2014; Willows & Rockey, 2018; Abhayawansa *et al.*, 2019), show a muted reaction to the integrated report release, when we use the timing of release of recommendations as an indicator of reaction. The subsequent incorporation of forecast accuracy into our calculations left the conclusion unchanged. Both the most and least accurate analysts in our sample were found to release their recommendations before integrated reports are published. More specifically, for H1.a, both the structural model and the regression model show no significant relationship with the quality of analysts' forecasts. Notably, the structural model used latent variables with multiple indicators for both integrated report quality and forecast decision quality. The latter comprised both forecast accuracy as well as the dispersion of analysts' forecasts. The findings were unchanged when only forecast accuracy was used, indicating that the findings are robust to alternate measurement approximations. The insights from the interviews strongly support the findings from the quantitative analysis. They indicate that analysts occasionally use integrated reports in preparation for meetings with management. Furthermore, it emerged that analysts prefer to use the financial statements and/ or more frequently released financial information contained in SENS announcements. The direction of the relationship (negative) was the same in both the structural model and the regression model. This inverse association between report quality and forecast quality suggests that better quality reports are (insignificantly) associated with poorer quality forecasts. These findings arise despite integrated reports being hailed as a revolutionary development in corporate governance (Eccles *et al.*, 2019).

Our second research objective was to evaluate the relationship between integrated report quality and analysts' biases. Specifically, the study hypothesised that bias has a significant effect on the forecast quality (H2). The direction and significance of the relationships were the same for the regression analysis and the structural model. However, the results from the analyses showed different directional relationships between each respective bias and the quality of integrated reports. Table 19 shows that, in some instances, the quantitative and qualitative analyses were divergent. The discrepant findings regarding the availability bias warrant further interrogation. Regarding availability (H2.a.), it is conceivable that the findings indicate that analysts always prioritise most recent information when providing forecasts and recommendations. This may be because they want to provide new information to the market. Indeed, with the volatility of the JSE (Rupande *et al.*, 2019), prioritising the influence of most recent circumstances may be the most rational alternative. The positive relationship may indicate that, when reports are of a good quality, analysts are more inclined to use the information contained therein. Overall, the quantitative analysis indicates that quality of integrated reports has varying impacts for respective biases, with all but one relationship being insignificant. These findings suggest an overall lack of moderation of quality of integrated reports on analysts' bias. Notably, in this study, the biases were calculated in relation to each company. This was because the integrated report quality scores were provided per company. The approach is similar to that of Barth *et al.* (2017) in which a "bias" variable was computed in relation to each company. However, prominent studies on analysts' bias are conducted with the analyst as the subject of analysis (Bernhardt *et al.*, 2006; Ahmed & Flint, 2020), and not aggregated by company. It is possible that the measurement implications of this study's design had implications for the significance levels relating to the relationship between report quality and bias.

Our final research objective was to evaluate the relationship between biases and the quality of analysts' forecasts. Specifically, H3 was disaggregated into sub- hypotheses which dealt with each respective bias. The quantitative analysis makes use of ex post trading data. As such, we cannot distinguish between spurious and intentional herding (Bennet *et al.*, 2003; Guo *et al.*, 2020). The findings from the interviews provides further detail on the type of herding that occurs. Analysts incorporate the consensus in their process of formulation of forecasts as a form of rigour. They consider the consensus to be a form of information and they want to take all possible information sources into account. This process is less aligned to the argument of common information, often proffered for spurious herding. We conclude that herding (most likely intentional) reduces the informational value of analysts' forecasts.

We also note discrepant findings where the quantitative results show a positive relationship between loss aversion and forecast quality. We would expect that the reluctance to issue downward revisions, despite having supporting data (we discussed share price movements in the interview), should lead to poorer quality forecasts. Yet, a positive association between loss aversion and forecast quality was noted.

In situations where discrepant findings are present, Creswell and Plano-Clark (2018) suggest that, instead of asking which method is right, the researcher should explicate why they may have more trust in one form of data or analysis over the other. In this manner, the divergence can be an avenue for further enquiry. For the present study, considering the model fit results (acceptable, but not good), issues with endogeneity and varying directional relationships between the biases and other variables in the models, the qualitative analysis provided required context to enable meaningful inferences.

Chapter 5: Conclusion and areas for future research

The present interdisciplinary study included various types of data and both qualitative and quantitative analyses. Yet, a common theoretical framework – the information environment – provided a common theoretical basis from which the various strands of research could be mobilised to provide new insights. It is therefore necessary to reflect on how the research objectives, outlined in Chapter 1, were achieved. This reflection is contained in Section 5.1. of this chapter. Section 5.2. details the contributions of the study. These contributions were outlined in Chapter 1 and are discussed with greater granularity as they include reference to specific findings. The study's limitations are acknowledged and discussed in Section 5.3.

Areas for future research are developed in each of the sections outlined in the preceding paragraph. Firstly, future research is recommended based on the findings in relation to each of the research objectives. Secondly, the study's contributions are further demonstrated as additional future research topics are developed based on the theoretical, methodological and practical implications of the present findings. Finally, we suggest future research endeavours which may address the limitations of the present study.

5.1. Reflection on the achievement of research objectives.

As introduced in Section 1.5. Research Objectives, the research questions in this study are:

RQ1: What is the effect of the quality of integrated report information on the market?

RQ2: Does the quality of information in integrated reports influence analysts' proclivity to behavioural bias?

RQ3: What is the effect of behavioural bias on analysts' forecast decisions?

To answer RQ1, we evaluated the association between integrated report quality and the information environment. Based on consistent findings cross all methods of analysis, we conclude that the quality of information in the integrated reports has little to no effect on the analysts' decision-making processes. However, we stop short of declaring that integrated reports have little to no information value. The present study focused on analysts, who have access to management in investor presentations and conference calls, with the results of the interviews confirming that meetings with management is one of the key sources of information used by the analysts. The access to management may therefore be viewed as a confounding factor in the evaluation of the effect of the quality of integrated reports. Pearl and Mackenzie (2019) use the example of clinical drug trails to illustrate the impact of a confounding factor such as lifestyle or diet. They explain that, in such evaluations of cause and effect, the researcher would typically use a control group of patients who do not receive the drug. Although the present research did not seek to make causal inferences, the analysts' access to management is analogous to a confounding factor in the evaluation of the use of the integrated reports. The present research focused on sell-side equity analysts, a choice that is motivated in Section 1.1 and 1.5. of Chapter 1. Research which employs a "control group" of users of company information, who do not have access to management, would be an insightful extension of the current research, as it would "control" for access to management.

The researchers considered the possibility that analysts use the integrated reports over time, to improve their understanding of the business of the firm. Then, once they understand the way the company operates, they defer to more timely information. However, this manner of use of the annual integrated reports would have been a possibility based only on the results of the structural equation model. However, being a mixed methods study, the researchers were able to discuss the analysts' use (or non-use) of integrated reports with them directly, even regarding their initiation of coverage. The researchers were also able to employ alternate empirical methods to confirm the non-use of integrated reports by analysts. For example, graphs showing the timing of recommendation releases (Figure 16 and 17) show a muted reaction to the release of integrated reports. Table 13, which compares the most and least accurate analyst, show that neither of them used the integrated reports before releasing their recommendations.

To answer RQ2, we evaluated the relationship between integrated report quality and analysts' biases. We concluded that the quality of information in the integrated report had little to no impact on reducing proclivity for bias of analysts. However, the varying directional results between the integrated report quality and each respective bias indicates the potential for future research which focuses on the impact of report quality on each respective bias. The present study provides an extension to Barth *et al.* (2017) in which one bias variable was used. Yet, given our findings, we propose that even further extensions are required to provide more detail on the relationships between each bias.

To answer RQ3, we evaluated the relationship between each behavioural bias and the quality of analysts' forecasts. As with the second research objective, the quantitative analysis yielded directional results that differed across the biases. Therefore, the context required for meaningful inferences was obtained from the qualitative analysis. This complementary methodological feature is a key motivation for the use of a convergent mixed methods design (Johnson & Onwuegbuzie, 2004). In synthesising the results from the quantitative and qualitative analysis on the relationship between loss aversion and forecast quality, discrepant findings were recorded, and directions for future research have been identified.

5.2. Contributions of the study

Contributions of the study were briefly outlined in Section 1.7. of Chapter 1. This section incorporates the literature review and findings of the study to demonstrate its contributions in detail. As in the preceding sections of this chapter, the contributions are also supported by potential areas for future research.

5.2.1. Theoretical

Whilst there exist studies on the use of integrated reports and studies on analyst bias, to the researchers' knowledge, and at the time of writing, there is no research that connects these two strands of research. Yet, it appears to be a natural extension of the research, when one considers the role of integrated reports concurrently with the implications of uncertainty in the markets. There is a plethora of research that connects bias to uncertainty (Kim & Pantzalis, 2003; Zhang, 2006; Kim, Ryu & Yang, 2021), especially the seminal work of Kahneman and Tversky (1974). In addition, studies which evaluate the informational benefits of integrated reports abound (for example, Barth *et al.*, 2017; Eccles *et al.*, 2019; Abhayawansa *et al.*, 2019). By using the information environment as a common theoretical base, we present a new strand of research, which connects bias to information quality. Our findings indicate an increased proclivity for bias in interactions with management in meetings and investor roadshows. We posit that a large portion of the information conveyed in these interactions could be provided in integrated reports, which are intended to provide detail about the long-term value creation strategy of the business to providers of financial capital (IIRC, 2021).

To the researchers' knowledge, and at the time of writing, the current study is the first to present an analysis from interviews with sell-side equity analysts who cover JSE-listed companies. The research on analyst recommendations is dominated by empirical analyses involving ex-post trading data. This trend is apparent even for JSE-focused research (for example, Ahmed and Flint, 2020). The interview sample of Abhayawansa *et al.* (2019) included only three analysts who covered JSE listed companies. The present research, by virtue of its sole focus on analysts who covered JSE-listed companies, presents important nuances from the information flows (detailed in Sections 4.2.9 to 4.2.12. of Chapter 4) in this market.

One of the relationships evaluated in this study is that between integrated report quality and returns on equity capital. Similarly, Barth *et al.* (2017) explored the economic consequences of integrated report quality. In doing so, they matched report quality scores per year to indicators such as the cost of capital. In turn, the cost of capital was measured using the share price *at the integrated report release date*. In the article, a footnote contains the explanation that to determine when the integrated report is published, JSE SENS announcements were used. Notably, however, when firms do not announce the release date of the integrated report, the annual report release date was used. This substitution of report release dates has the potential to confound the effect of the annual report with the effect of the integrated report. The findings in the event study of Willows and Rockey (2018) and this study's descriptive statistics on the timing of the recommendation release date show that there is a notable difference in reaction to the release of the annual report and the integrated report. Our interviews with analysts provide further substantiating evidence in this regard. Analysts find the information in the annual report and SENS announcements more useful than the information in the integrated reports.

Given these observations, we posit that future studies that seek to connect integrated report quality with economic effects (such as cost of capital) should have as their primary theoretical underpinning, the concept of integrated thinking, the analysis of which is not constrained by distinctions between the time of release of annual reports and integrated reports. As detailed in Section 2.5. of Chapter 2, integrated thinking refers to the integration of decision-making capabilities in the organisation to drive long term value creation activities. Although the IIRC proposes integrated thinking as being a concomitant of integrated reporting, academic studies that interrogate this relationship are still emerging (Dimes & de Villers, 2023; Ecim & Maroun, 2023). We therefore encourage future endeavours in this regard, as they can provide a less equivocal basis for studies on the benefits of the integrated report quality.

In this study, we have described the dual role that analysts play in the information environment, being both consumers and producers of information. Yet, we note from the literature review that the research on analysts in emerging economies, including South Africa, is scant. Ahmed and Flint (2020) provided one of the few studies to focus on the accuracy of analysts in South Africa. A strand of research is emerging which considers the information impact of analysts in the Indian emerging economy (Chaudhury *et al.*, 2022). Whilst the JSE is also an emerging economy, its corporate governance structures have been lauded as pioneering, especially with regards to the effective mandating of integrated reporting (Eccles *et al.*, 2019). The impacts of these advances on the equity markets can be evaluated by considering the inputs, processes and outputs of analysts. The present research takes a step in addressing this research gap, with its detailed evaluation of analysts' forecast data.

Section 2.2. of Chapter 2 details the various roles that analysts play in the information environment. Recently, there has been an increase in research focus on the monitoring role of the analyst (Brown *et al.*, 2015; Chen et al., 2015; Chen *et al.*, 2017). The theme of declining analyst coverage emerged in the interviews. Research exists on the decision to initiate coverage (see for example, Hettler *et al.*, 2023). However, we posit that research on the emerging market context would have a greater contribution to offer than similar research in a developed market.

We present empirical evidence in this potential research endeavour, by ruling out the quality of integrated reports as a potential contributor to the coverage decision. In Section 3.4.2, we identified the companies which attracted the greatest analyst following, Anheuser-Busch Inbev and BTI. Notably, neither Anheuser-Busch Inbev nor British American Tobacco have their primary listings on the JSE. According to JSE listing requirements, companies with a secondary listing are not required to produce an integrated report. However, these companies' corporate reports were included in the EY integrated reporting evaluation. Barth *et al.* (2017) posit that even though such companies are not subject to mandatory integrated reporting requirements, their corporate reports are still consistent with the principles of integrated reporting. In 2018, the report of British American Tobacco was identified as "Good" by EY's panel of adjudicators. However, in 2017, the reports of Anheuser-Busch Inbev were rated as "Progress to be made". The observed differences in "integrated report" quality scores of companies which have both attracted large analyst following, provides further evidence that disclosures required in integrated reports are not drivers of analyst interest in a company.

5.2.2. Methodological

Finance research appears to be dominated by the positivist paradigm which prioritises measurement and inferences drawn from quantified results. This is evidenced by the slew of research that uses measurement approximations or survey results to quantify bias (see Section 2.14.3). These approximations are then used in a regression model or in a factor analysis. To a large extent, the present study also attempts to quantify bias and then uses structural equation modelling to evaluate its associations. However, consistent with the pragmatic paradigm which prioritises the use of the most appropriate method to answer research questions and propose solutions to real-world problems, the present study also incorporates interviews from analysts. There are certainly studies that use interview data (see for example Chaudhury *et al.*, 2022) but, based on our analysis of the bias literature (contained in Section 2.11. of Chapter 2), these studies are not as prevalent as empirical studies. The approach to evaluating bias using interview data contributes to filling the lacuna of qualitative finance research. Therefore, the insights from the interviews, with specific focus on bias, presents a methodological contribution. This is notable as an interview guide that extracts relevant information, whilst not providing leading information must be carefully curated (Creswell & Poth, 2016), especially in the context of bias.

The use of both qualitative and quantitative methods also provides a methodological contribution. It answers the call by Ahmad (2020) for mixed methods research to fully understand biases and their effect on investment decisions. In the present study, results from the quantitative and qualitative analysis were considered concurrently, in order to arrive at a conclusion. This type of analysis is particularly valuable, given the observation that several biases can be used as an explanation for a single type of trading behaviour (Liu *et al*., 2022). We also provide a synthesis of the relationships between the biases in Section 2.11.5. of Chapter 2 and show the potential for conflicting results when inferences are based solely on measurement approximations.

As detailed in the seminal work of Asquith *et al.* (2005), the content of analyst reports also conveys rich detail about their use of information. However, besides Mokoaleli-Mokoteli *et al.* (2009), the research which examines analyst reports for evidence of bias is scant. Further research which focuses on the content of analyst reports has the potential to allow for enquiry into analyst bias, without the inherent limitations of summarised forecast and trading data.

Structural Equation Modelling has emerged relatively recently in finance and corporate reporting studies (Smith & Langfield-Smith, 2004). Specifically, the treatment of the integrated report quality as a latent construct, represents a notable differentiation from Barth *et al.* (2017) whose objectives closely aligned with some of ours. Our use of this method of analysis therefore presents a methodological contribution. A further contribution is made with the calculation of measurement indicators for the latent variables. The data used for a SEM analysis is usually survey data, with responses to Likert scale questions. The present research instead uses measurement approximations (from prior research) as indicators for each latent variable. We posit that this represents a notable yet logical (see the use of latent variables in Titman and Wessels, 1988) deviation from the prior research.

5.2.3. Practical

In Chapter 1, we cited the detachment of academic research from practice due to the lack of interaction between practitioners and researchers (Hopwood, 2007; Coleman, 2014). Our semi-structured interviews with analysts were sufficiently flexible to allow for the emergence of relevant themes, not extensively covered in the prior literature. We also calculated unconventional descriptive statistics from the analyst forecast data to further explore insights from the interviews (for example, see Table 11). The study therefore makes several practical contributions.

In the section on “analyst incentives” and “difficulties in the sell-side research industry” the issue of corporate commissioned (sponsored) coverage is discussed. To date, and to the researcher’s knowledge, there is no research on this type of coverage in the context of JSE-listed forms. This is a notable area for further research, given the dominance of trades relating to large firms on the JSE. There is therefore great potential for sponsored coverage in the South African context, with its high levels of institutional ownership (Obagbuwa, Kwenda & Akinola, 2021). Therefore, there is also an imperative for concomitant academic research on sponsored coverage, which has the potential for great informational consequences.

These informational consequences are significant in weaker information environments. Although Malola and Maroun (2019) found no significant association between integrated report quality and firm size, the interviews with analysts in this research suggest that better information environments are required to enhance liquidity in the South African equity capital market. Analysts' minimal use of integrated reports is evident from prior research and affirmed in the current research. A comparison of the information content and format of these commissioned reports to the information contained in integrated reports may highlight aspects of the analyst reports that are more useful to investors. This is significant because companies are willing to pay for additional analyst coverage, and these reports are provided to the market over and above corporate reports that are mandatory for listed companies.

A rudimentary content analysis of five commissioned research reports provides the initial indication of the forecasts being optimistic. A more rigorous exploratory content analysis, deferred to future studies, will be the first such analysis in the South African and possibly in the developing market context.

There has been limited quantitative research on the buy-side analysts (Gu *et al.*, 2022), with the qualitative research being scarcer. Chaudhury *et al.* (2022) provided one of the few evaluations of how buy-side analysts use the information provided by sell-side analysts in their investment decisions. Amongst the motivations for the study, the authors cite the intriguing context of the developing Indian market where information flows are different to the developed economies. Future research which focuses on the potentially mediating role of the buy-side analyst on the bias of sell-side analysts could contribute to the scant literature on buy-side analysts in South Africa. This research would be valuable considering the importance of the buy-side researchers on institutional investing activities on the JSE.

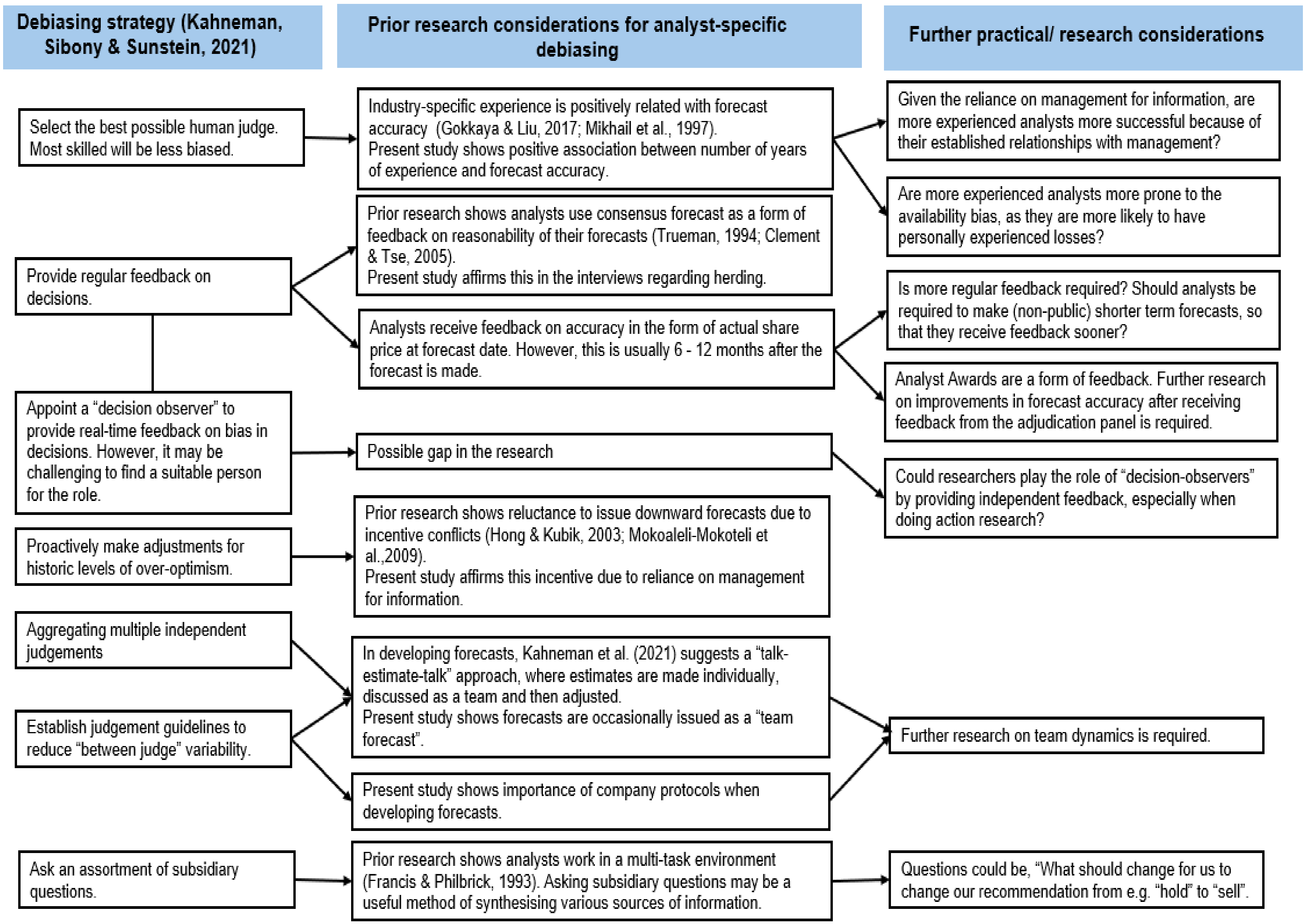
During the interviews, it became apparent that the interaction between sell-side and buy side analysts was an area that required research interest, especially given that it is the buy side analysts whose research is more influential on institutional investments. During the interviews, one of the participants who had worked as a sell-side analyst and was employed as a buy side analyst at the time of the interview, suggested that the researcher focus specifically on buy side researchers in future projects. Indeed, the themes which emerged on buy side researchers suggest the potential for future research on the buy side analysts, who are less likely to be prone to some of the biases which exist because of the nature of the sell-side analysts' role in financial institutions. Interestingly, one of the interview participants asserted that buy side analysts are not free from bias. The participant bemoaned the tendency for buy side analysts to favour sell-side research that confirms their pre-formed view of companies for investment purposes. This proclivity for confirmation bias on the part of the buy side researcher presents an area for future research.

The emergence of the interview theme of the influence of company protocols opens up avenues for future research that contributes to the current literature on herd behaviour. When complying with company guidelines regarding recommendations, herding amongst analysts in the same company or in companies with similar investment philosophies (consistent with the notion of common information from Bikhchandani and Sharma, 2000 and spurious herding as discussed in Guo *et al.*, 2020) represents a rational behaviour by the analysts. Similar research on the impact of institutional investment philosophies in the South African context has contribution potential, given the dominance of institutional trades on the JSE.

For any research that investigates the possibility of bias, a natural extension is to determine how these biases can be avoided. Several studies make a practical contribution by simply identifying the possibility for bias, so that market participants are aware of their biases and adjust their judgements accordingly. The results of the present study show that the quality of integrated reports does not reduce bias. We also show the possibility for loss aversion, herding and availability to affect forecast accuracy. To make an incremental contribution to the literature, and to enhance the practical relevance of our findings, we create a framework with debiasing strategies specifically for analysts. This framework is based largely on the work of Kahneman, Sibony and Sunstein (2021), in the recent book titled, “Noise: A Flaw in Human Judgement”, specifically in the section titled, “Improving Judgements”. We use the debiasing strategies proposed in the book as the basis for our framework. We then include relevant findings from prior research and the current study to propose debiasing strategies specifically for analysts, in the current information environment.

It is evident that the proposed debiasing strategies can be applied to the processes of sell-side equity analysts. Prior research on analysts, as well as the findings of this study can be mobilised to translate theoretical suggestions to strategies for real life contexts. For example, Kahneman et al. (2021) suggest that providing regular feedback on decisions can reduce bias. Feedback on the accuracy of 6-month price forecasts can be received only 6 months after the forecast is made. Similarly, although the Financial Mail analyst awards also provide a form of feedback, the awards are held annually. Further practical considerations therefore include the possibility of issuing non-public forecasts more frequently so that a comparison of actual to forecasted prices (which is a form of feedback) can also be done more frequently. Similarly, the approach of “talk-estimate-talk”, as explained in Kahneman et al. (2021 p.262) may be feasible with teams of analysts. Given the potential for improved judgments in teams of analysts, further research on team dynamics amongst sell-side equity analysts is warranted. Additional suggestions and areas for future research are presented in Figure 18: Debiasing framework applied to analysts.

Figure 18: Debiasing framework applied to analysts. (Source: Author's own)



5.3. Limitations of the study

The present study has made several valuable contributions. Yet, like any study, our results are subject to certain caveats. The rest of this section describes the limitations and suggests future research endeavours that may mitigate them.

The use of IR quality scores has increased this study's reliability. However, it comes at the cost of having a large number of companies, across various industries. Due to these sample size constraints (as with Barth *et al.*, 2017), it was not possible to reliably compare forecast accuracy by industry. Future research will provide a value extension by including industry effects with a larger sample, especially given the findings of Harris and Wang (2019) that analysts' forecasts are significantly more accurate than other model-based forecasts for the telecommunications and financial services industries. The relatively complex nature of these industries suggests that analysts' industry expertise is more valuable when they cover companies in certain industries. A related limitation is that it includes only JSE listed companies. However, the analysts that were interviewed could have covered other companies.

The results of the quantitative analysis showed varying directional relationships between integrated report quality and each of the biases and between each bias and analyst forecast quality. Like any quantitative analysis, these results are likely to vary according to the chosen measurement approximations. Section 2.14.2. highlighted the variety of measurement approximations for biases and importantly, showed the relationships between the biases and the principles used to develop measurement approximations for them. We acknowledge the potential for the diverse directional relationships in this study to be explained by the relationships between biases and across measurement approximations. However, given the results which show discriminant validity, we acknowledge a limitation of the quantitative analysis being that alternate measurement approximations would have provided different results.

The results of our SEM analysis indicated an endogeneity issue with the availability variable. In response, we use Gaussian copulas and even ran a regression model in which we excluded the availability variable. As described in Section 4.3.3. of Chapter 4, the impact of endogeneity in SEM analyses has been considered to varying extents in the prior relevant research. For models which incorporate bias, as in this study, we posit that the relationships between the biases or measurement approximations for the biases may have an impact on the robustness of results to issues of endogeneity. In the present research, we discussed commonly used measurement approximations, and relationships between them in Section 2.14.3. of Chapter 2. Future research that specifically focuses on endogeneity issues in SEM which arise from the combinations of these measurement approximations is likely to provide a methodological contribution.

The present research focused on share price forecasts, the accuracy and determination thereof. Further research could extend to earnings forecasts, similar to that of Harris and Wang (2019). The differences between the forecasts of earnings and share prices are likely to contribute to the behavioural research on forecasting capital market performance compared to internal firm-specific performance. The theoretical context of information content from share prices compared to the information content from fundamental information (Harris & Wang, 2019) provides an intriguing area for future research, given the findings of the present research. In the present research, it emerged that technical analysis was used by some participants in their share price forecasts. Research which focuses on the forecasts of earnings specifically, has the potential to inform corporate reporting practice.

The focus of this study was on integrated report quality and analyst bias. However, we could not ignore the potential effect of analyst experience, which has attracted strong focus in the prior literature. Section 2.12.2. on Analyst Experience, outlines the vast literature on the impact of the analysts' personal characteristics. For example, the gender of sell-side equity analysts has also attracted research attention (for example, Kumar, 2010). During the present study, Participants 10 and 12 mentioned the difficulties they had experienced as females in what they perceived as a male-dominated industry. In our sample, only 15% of the analysts were coded by the researcher as being female based on their LinkedIn profiles. Whilst such insights about the personal characteristics of analysts are intriguing, due to scope delimitations, they are tangential to the scope of the current study. Additional, exploratory analysis was undertaken to determine whether there is potential for further research on the topic. We found that level of qualification and gender were both insignificantly related to forecast accuracy. Further, dedicated studies on the topic are warranted.

There is a growing strand of research that investigates the influence (or lack thereof) of the sell-side researcher's analysis on the investment decision making of the buy -side researchers (Imam and Spence, 2016, Chaudary, Sahoo and Dawar, 2022). Specifically, Chaudary *et al.* (2022 p.637) refer to the investment processes and interactions between buy and sell-side analysts as a "black box". It is beyond the scope of the current research to investigate the influence of sell-side analysts' recommendations and research on the ultimate investment decisions of buy-side analysts. However, the emergence of this theme in the interviews suggest that the interaction between the buy side and sell-side researchers is a topic worthy of a dedicated study.

5.4. Concluding remarks

The journey of this study concludes by reflecting on one of its earliest signposts, the thesis statement:

The quality of integrated reports impacts the information environment in the equity capital markets. Where the information environment is poor, investors will resort to the use of heuristics in their decision-making.

The statement was predicated on the notion that market participants are likely to substitute heuristics for information, when the information environment is poor (Tversky & Kahneman, 1974). The results from our mixed methods approach show a lack of use of integrated reports by sell-side equity analysts. They rely instead on direct engagements with management, in which they trust their heuristics to gauge the credibility of management and their assertions about the future of the company. Analysts who covered companies that produced unreliable financial information appear to be most weary of the likelihood of the audit failures or misstatements, evidence of the availability bias. Analysts appear to herd around consensus forecasts, which they view as a more valuable source of information than the integrated report. As an initial step in the new direction for future research, we propose a framework of bias mitigating strategies for analysts, based on Kahneman *et al.* (2021), the present study's literature review and its findings. Future research which expands on each mitigating strategy is likely to be of practical relevance, further answering the calls for practitioner-focused research. In addition, the issues of declining analyst coverage and concomitant increase in company-sponsored coverage are largely unexplored in the South African context, despite having far-reaching implications for the information environment.

In evaluating the thesis statement, the study offers both theoretical and practical insights, particularly in the context of JSE-listed companies. Besides emphasising the limitations of integrated reports, debiasing strategies have been proposed, specifically for sell-side analysts, drawing from the most recent work of Kahneman et al. (2021). These strategies aim to improve forecast accuracy and decision-making processes, with implications for future research on sell-side analysts.

5.5. Self-reflections on the research journey

Studying towards a doctorate represents an important milestone in the life of a student, as the associated uncertainty is concomitant with the opportunity for self-development (Seetharam, 2016). As a Chartered Accountant with experience in the practical application of finance theories, my motivation for this thesis came from a curiosity about why smart, well-informed individuals sometimes make poor decisions. Kahneman et al. (2021) refers to the importance of processes which foster good decision-making. Having witnessed both effective and flawed decision-making processes during my time in practice, I was driven to explore this phenomenon in greater depth.

From a theoretical perspective, this study required me to position myself within two distinct (yet related) research communities – corporate reporting and behavioural finance. This offered me the opportunity to navigate these fields and reflect on where I might contribute most meaningfully with current and future research endeavours. From a methodological perspective, as with Muncey (2009), I had to defend non-dominant methodological stances in each of these communities, which provided an opportunity for personal growth and challenged me to sharpen my understanding of the merits and pitfalls of the various approaches. It became clear that a pragmatic paradigm best aligned with my research objectives as I was not biased towards a single methodology. Instead, my focus was on answering the research question in the most effective way possible. From the entire process, perhaps one of the most valuable learnings was that research aimed at improving real-world decision-making must remain closely connected to the realities of practice.

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Appendix A: Extracts from the Integrated Reporting Framework

Guiding Principles

The seven Guiding Principles underpin the preparation and presentation of an integrated report, informing the content of the report and how information is presented.	
Strategic focus and future orientation	An integrated report should provide insight into the organization's strategy, and how it relates to the organization's ability to create value in the short, medium and long term and to its use of and effects on the capitals.
Connectivity of information	An integrated report should show a holistic picture of the combination, interrelatedness and dependencies between the factors that affect the organization's ability to create value over time
Stakeholder relationships	An integrated report should provide insight into the nature and quality of the organization's relationships with its key stakeholders, including how and to what extent the organization understands, takes into account and responds to their legitimate needs and interests.
Materiality	An integrated report should disclose information about matters that substantively affect the organization's ability to create value over the short, medium and long term.
Conciseness	An integrated report includes sufficient context to understand the organization's strategy, governance, performance and prospects without being burdened with less relevant information
Reliability and completeness	An integrated report should include all material matters, both positive and negative, in a balanced way and without material error.
Consistency and comparability	The information in an integrated report should be presented: • On a basis that is consistent over time • In a way that enables comparison with other organizations to the extent it is material to the organization's own ability to create value over time

Fundamental Concepts

2.1. The Fundamental Concepts underpin and reinforce the requirements and guidance in the <IR> Framework.

2.2. An integrated report explains how an organization creates, preserves or erodes value over time. Value is not created, preserved or eroded by or within an organization alone. It is:

• Influenced by the external environment

• Created through relationships with stakeholders

• Dependent on various resources.

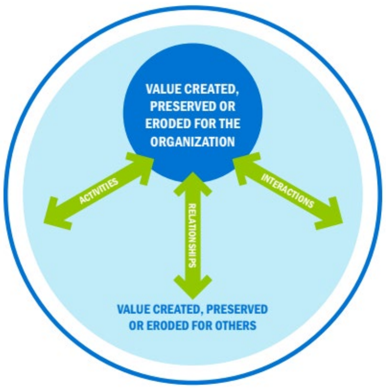
2.3. An integrated report therefore aims to provide insight about:

• The external environment that affects an organization

• The resources and the relationships used and affected by the organization, which are referred to collectively in the <IR> Framework as the capitals and are categorized in Section 2C as financial, manufactured, intellectual, human, social and relationship, and natural

• How the organization interacts with the external environment and the capitals to create, reserve or erode value over the short, medium and long term.

Figure 1. Value created, preserved or eroded for the organization and for others



Content Elements

An integrated report includes eight Content Elements that are fundamentally linked to each other and are not mutually exclusive:	
Organizational overview and external environment	What does the organization do and what are the circumstances under which it operates?
Governance	How does the organization's governance structure support its ability to create value in the short, medium and long term?
Business model	What is the organization's business model?
Risks and opportunities	What are the specific risks and opportunities that affect the organization's ability to create value over the short, medium and long term, and how is the organization dealing with them?
Strategy and resource allocation	Where does the organization want to go and how does it intend to get there?
Performance	To what extent has the organization achieved its strategic objectives for the period and what are its outcomes in terms of effects on the capitals?
Outlook	What challenges and uncertainties is the organization likely to encounter in pursuing its strategy, and what are the potential implications for

	its business model and future performance?
Basis of presentation	How does the organization determine what matters to include in the integrated report and how are such matters quantified or evaluated?

Source: IIRC (2021)

Appendix B: Extract of raw data used in the study

Recommendation - level

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	From: Price Targets vs Actual Modified 3 April, data scores prices (2)												
2	ID	Co	Text	CoYr	Year End	AR Release	IR Release	Firm Name	Analyst	Recommendation	Date	Target Price	Actual Price Forecast
249	AMS16Mor	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS16	31 Dec 16	15 Feb 17	01 Mar 17	Morgan Stanley	Christopher Nicholson	Equalwt/In-Line	15 02 2017	34 000.00	32 350
250	AMS16JP	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS16	31 Dec 16	15 Feb 17	01 Mar 17	JP Morgan	Dominic O'Kane	neutral	15 02 2017	48 000.00	32 350
251	AMS16NOA	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS16	31 Dec 16	15 Feb 17	01 Mar 17	NOAH Capital Markets	Rene Hochreiter	buy	15 02 2017	51 500.00	32 350
252	AMS17Gol	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS17	31 Dec 17	19 Feb 18	09 Mar 18	Goldman Sachs	Abhinandan Agarwal	Sell/Neutral	23 03 2018	25 000.00	33 893
253	AMS17Ned	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS17	31 Dec 17	19 Feb 18	09 Mar 18	Nedgroup Securities	Leon Esterhuizen	buy	20 02 2018	50 000.00	35 780
254	AMS18Gol	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	Goldman Sachs	Abhinandan Agarwal	sell	29 03 2019	45 000.00	73 615
255	AMS18Inv	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	Investec	Nkateko Mathonsi	buy	27 03 2019	85 000.00	78 800
256	AMS18Ren	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	Renaissance Capital Group	Steven Friedman	hold	26 03 2019	71 000.00	79 500
257	AMS18Mor	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	Morgan Stanley	Christopher Nicholson	Underwt/Attractive	25 03 2019	65 000.00	79 686
258	AMS18NOA	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	NOAH Capital Markets	Rene Hochreiter	buy	08 03 2019	202 100.00	75 139
259	AMS18Ned	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	Nedgroup Securities	Arnold Van Graan	hold	05 03 2019	90 000.00	74 391
260	AMS18SBG	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS18	31 Dec 18	18 Feb 19	13 Mar 19	SBG Securities (Pty) Ltd	Leroy Mnguni	sell	26 02 2019	65 000.00	73 987
261	AMS19Ned	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS19	31 Dec 19	17 Feb 20	11 Mar 20	Nedgroup Securities	Arnold Van Graan	hold	30 03 2020	130 000.00	71 884
262	AMS19Mor	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS19	31 Dec 19	17 Feb 20	11 Mar 20	Morgan Stanley	Christopher Nicholson	Equalwt/Attractive	27 03 2020	80 000.00	72 843
263	AMS19JP	AMS	'[Share prices.xlsx]AMS'!A$4:J$3999	AMS19	31 Dec 19	17 Feb 20	11 Mar 20	JP Morgan	Dominic O'Kane	neutral	27 03 2020	70 000.00	72 843
264	ANG15Gol	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	Goldman Sachs	Eugene King	buy/attractive	24 03 2016	30 000.00	20 198
265	ANG15Deu	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	Deutsche Bank	Patrick Mann	buy	22 03 2016	23 000.00	21 180
266	ANG15Ren	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	Renaissance Capital Group	Steven Friedman	sell	18 03 2016	12 300.00	20 625
267	ANG15Mor	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	Morgan Stanley	Leroy Mnguni	Overwt/In-Line	15 03 2016	22 000.00	20 655
268	ANG15Mac	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	Macquarie	James Oberholzer	outperform	15 03 2016	22 000.00	20 655
269	ANG15HSB	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	HSBC	Derryn Maade	buy	14 03 2016	26 300.00	20 439
270	ANG15RBC	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	RBC Capital	Richard Hatch	sector perform	08 03 2016	20 000.00	20 400
271	ANG15SBG	ANG	'[Share prices.xlsx]ANG'!A$4:J$3999	ANG15	31 Dec 15	22 Feb 16	31 Mar 16	SBG Securities (Pty) Ltd	Adrian Hammond	hold	23 02 2016	15 500.00	18 050

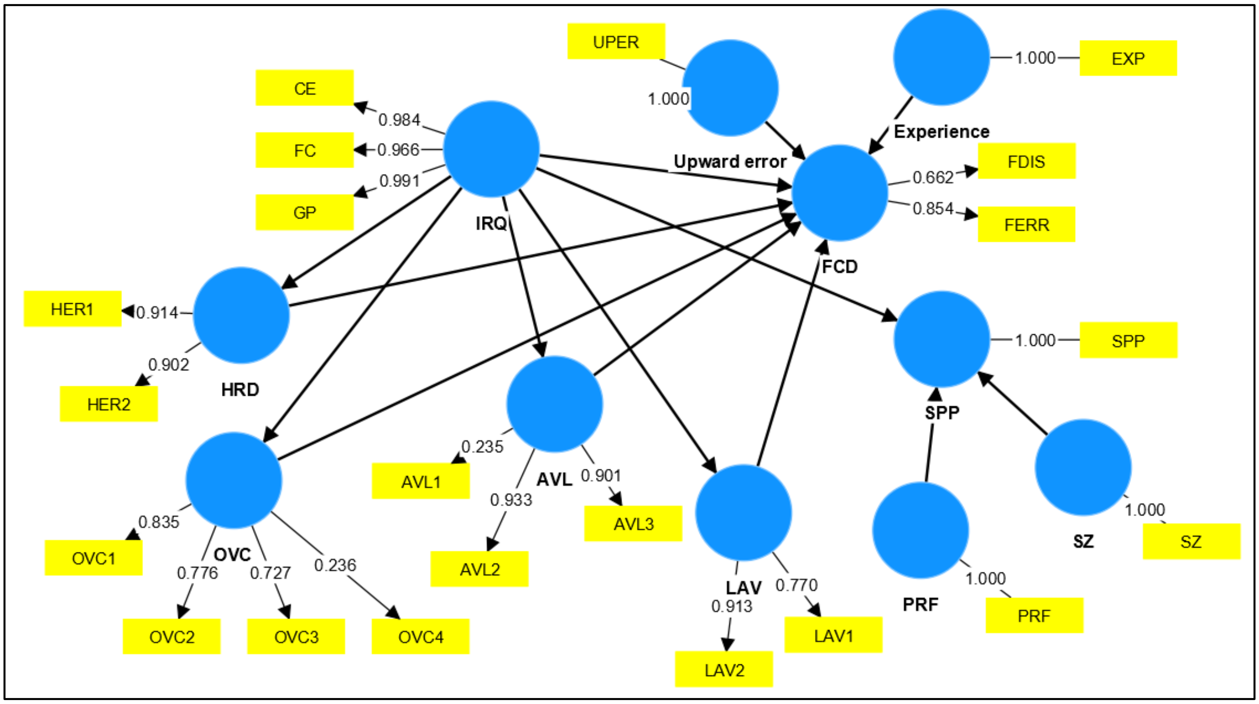
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL
1			AR+T0	IR+T0					18	19	20	21	20.00	23.00	70.00	24.00	80.00	26.00	26.00	26.00	26.00	sheet with	29	sheet with a	31	32
2	ce	Number of days	Forecast Date LESS	Forecast Date less IR	Before AR Date?	Date Actual Price	Weekday	Actual Price	FERR	F_ERR	FDIS	F_DIS	FC_RAW	FC	GP_RAW	GP	CE_RAW	CE	UPERR	EXP	SPP	PRF	LN_PRF	TA	LN_TA	AVL1
249	0	14	0.00	-14.00	FALSE	15 02 2018	5	33 824	192.1818182	5.258441894	0.00010688	-9.14	13.00	0.65	51.00	0.73	60.33	0.75	0.5	19		1.36	0.307485	77697000	18.168327	0.028825
250	0	14	0.00	-14.00	FALSE	15 02 2018	5	33 824	2.386004515	0.869620216	0.00010688	-9.14	13.00	0.65	51.00	0.73	60.33	0.75	0.5	21		1.36	0.307485	77697000	18.168327	0.028825
251	0	14	0.00	-14.00	FALSE	15 02 2018	5	33 824	1.913555103	0.648962822	0.00010688	-9.14	13.00	0.65	51.00	0.73	60.33	0.75	0.5	17		1.36	0.307485	77697000	18.168327	0.028825
252	3	18	32.00	14.00	FALSE	23 03 2019	7	83 500	1.427350427	0.355819878	0.00005657	-9.78	11.33	0.57	50.00	0.71	59.67	0.75	0.571	13		4.38	1.477049	80814000	18.207661	0.005013
253	0	18	1.00	-17.00	FALSE	20 02 2019	4	74 375	3.051282051	1.115561847	0.00005657	-9.78	11.33	0.57	50.00	0.71	59.67	0.75	0.571	11		4.38	1.477049	80814000	18.207661	0.005013
254	5	23	39.00	16.00	FALSE	28 03 2020	7	72 843	2.61620515	0.961724852	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	13		10.87	2.386007	89390000	18.308519	0.016432
255	0	23	37.00	14.00	FALSE	26 03 2020	5	72 836	5.98783295	1.789729569	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	17		10.87	2.386007	89390000	18.308519	0.016432
256	0	23	36.00	13.00	FALSE	25 03 2020	4	75 018	18.67048283	2.926943818	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	17		10.87	2.386007	89390000	18.308519	0.016432
257	6	23	35.00	12.00	FALSE	24 03 2020	3	61 206	16.13231418	2.780824352	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	19		10.87	2.386007	89390000	18.308519	0.016432
258	9	23	18.00	-5.00	FALSE	07 03 2020	7	94 764	0.882872475	-0.12457451	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	17		10.87	2.386007	89390000	18.308519	0.016432
259	1	23	15.00	-8.00	FALSE	04 03 2020	4	111 762	5.135649297	1.636206281	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	20		10.87	2.386007	89390000	18.308519	0.016432
260	7	23	8.00	-15.00	FALSE	26 02 2020	4	125 500	2.074380165	0.729662394	0.00001923	-10.86	8.67	0.43	42.67	0.61	52.00	0.65	0.273	12		10.87	2.386007	89390000	18.308519	0.016432
261	4	23	42.00	19.00	FALSE	30 03 2021	3	214 179	2.544328158	0.93386663	0.00003111	-10.38	15.00	0.75	55.67	0.80	64.00	0.80	0.111	20		24.33	3.19171	104020000	18.460094	0.008902
262	3	23	39.00	16.00	FALSE	27 03 2021	7	224 087	1.55522011	0.441617085	0.00003111	-10.38	15.00	0.75	55.67	0.80	64.00	0.80	0.111	19		24.33	3.19171	104020000	18.460094	0.008902
263	3	23	39.00	16.00	FALSE	27 03 2021	7	224 087	1.454288811	0.374516991	0.00003111	-10.38	15.00	0.75	55.67	0.80	64.00	0.80	0.111	21		24.33	3.19171	104020000	18.460094	0.008902
264	8	38	31.00	-7.00	FALSE	24 03 2017	6	13 942	0.868227675	-0.1413013	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	1		6.51	1.873339	7284000	15.801191	0.024922
265	0	38	29.00	-9.00	FALSE	22 03 2017	4	14 114	1.588341211	0.462690208	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	17		6.51	1.873339	7284000	15.801191	0.024922
266	5	38	25.00	-13.00	FALSE	18 03 2017	7	13 895	8.711598746	2.164655327	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	17		6.51	1.873339	7284000	15.801191	0.024922
267	5	38	22.00	-16.00	FALSE	15 03 2017	4	13 075	1.464985994	0.381845682	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	12		6.51	1.873339	7284000	15.801191	0.024922
268	5	38	22.00	-16.00	FALSE	15 03 2017	4	13 075	1.464985994	0.381845682	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	17		6.51	1.873339	7284000	15.801191	0.024922
269	9	38	21.00	-17.00	FALSE	14 03 2017	3	13 267	1.017954423	0.017795146	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	16		6.51	1.873339	7284000	15.801191	0.024922
270	0	38	15.00	-23.00	FALSE	08 03 2017	4	13 100	1.898550725	0.641090819	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	5		6.51	1.873339	7284000	15.801191	0.024922
271	0	38	1.00	-37.00	FALSE	22 02 2017	4	15 779	56.55555556	4.035223439	0.00017804	-8.63	12.33	0.62	52.33	0.75	63.33	0.79	0.647	14		6.51	1.873339	7284000	15.801191	0.024922
272	5	38	38.00	0.00	FALSE	31 03 2018	7	11 252	0.896716608	-0.1090154	0.00024516	-8.31	10.33	0.52	45.33	0.65	57.67	0.72	0.5	14		6.57	1.882514	7153000	15.783042	0.02439
273	0	38	36.00	2.00	FALSE	29 03 2018	5	11 252	1.975074601	0.68060617	0.00024516	-8.31	10.33	0.52	45.33	0.65	57.67	0.72	0.5	21		6.57	1.882514	7153000	15.783042	0.02439

	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS	AT	AU	AV	AW	AX
1	70.00	24.00	80.00	26.00	26.00	26.00	26.00	sheet with	29	sheet with a	31	32	33	34	35	36	37	38	39	40	41	42	43	44
2	GP_RAW	GP	CE_RAW	CE	UPERR	EXP	SPP	PRF	LN_PRF	TA	LN_TA	AVL1	AVL2	AVL3	OVC1	OVC1a	OVC2	OVC3	OVC4	HER1	HER2	LAV1	LAV2	LAV3
249	51.00	0.73	60.33	0.75	0.5	19		1.36	0.307485	77697000	18.168327	0.028825	-19.77	16.60556	0.078014	0.25	0.615385	0.076923	0	1.333333	0	1.333333	3	0.168865
250	51.00	0.73	60.33	0.75	0.5	21		1.36	0.307485	77697000	18.168327	0.028825	-19.77	16.60556	0.301627	0.25	0.615385	0.076923	0	1.333333	0	1.333333	3	0.168865
251	51.00	0.73	60.33	0.75	0.5	17		1.36	0.307485	77697000	18.168327	0.028825	-19.77	16.60556	0.396537	0	0.615385	0.076923	0	1.333333	0	1.333333	3	0.168865
252	50.00	0.71	59.67	0.75	0.571	13		4.38	1.477049	80814000	18.207661	0.005013	1.36	-1.1518	0.333333	0.5	0.5	0.5	0.03125	2	1	2	2	0.262385
253	50.00	0.71	59.67	0.75	0.571	11		4.38	1.477049	80814000	18.207661	0.005013	1.36	-1.1518	0.333333	0	0.5	0.5	1	2	0	2	2	0.262385
254	42.67	0.61	52.00	0.65	0.273	13		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	0.494463	0	0.571429	0.142857	0.025641	1	1	1	0.6	0.231492
255	42.67	0.61	52.00	0.65	0.273	17		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	0.045097	1	0.571429	0.142857	0.027027	1	1.068966	1	0.6	0.231492
256	42.67	0.61	52.00	0.65	0.273	17		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	0.202375	0.5	0.571429	0.142857	0.027778	1	1.107143	1	0.6	0.231492
257	42.67	0.61	52.00	0.65	0.273	19		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	0.26978	0	0.571429	0.142857	0.028571	1	1.148148	1	0.6	0.231492
258	42.67	0.61	52.00	0.65	0.273	17		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	1.270422	1	0.571429	0.142857	0.055556	1	3.1	1	0.6	0.231492
259	42.67	0.61	52.00	0.65	0.273	20		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	0.011074	0.5	0.571429	0.142857	0.066667	1	4.428571	1	0.6	0.231492
260	42.67	0.61	52.00	0.65	0.273	12		10.87	2.386007	89390000	18.308519	0.016432	4.38	-3.70232	0.26978	0	0.571429	0.142857	0.125	1	0	1	0.6	0.231492
261	55.67	0.80	64.00	0.80	0.111	20		24.33	3.19171	104020000	18.460094	0.008902	10.87	1.337032	0.392857	0	0	0.333333	0.02381	0.142857	1	0.142857	7	0
262	55.67	0.80	64.00	0.80	0.111	19		24.33	3.19171	104020000	18.460094	0.008902	10.87	1.337032	0.142857	0	0	0.333333	0.025641	0.142857	0	0.142857	7	0
263	55.67	0.80	64.00	0.80	0.111	21		24.33	3.19171	104020000	18.460094	0.008902	10.87	1.337032	0.25	0	0	0.333333	0.025641	0.142857	0	0.142857	7	0
264	52.33	0.75	63.33	0.79	0.647	1		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.402688	0	0.5	0.125	0.032258	2.2	1	2.2	5	0.403636
265	52.33	0.75	63.33	0.79	0.647	17		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.075395	0	0.5	0.125	0.034483	2.2	1.071429	2.2	5	0.403636
266	52.33	0.75	63.33	0.79	0.647	17		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.424898	0.5	0.5	0.125	0.04	2.2	1.25	2.2	5	0.403636
267	52.33	0.75	63.33	0.79	0.647	12		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.028638	0	0.5	0.125	0.045455	2.2	1.428571	2.2	5	0.403636
268	52.33	0.75	63.33	0.79	0.647	17		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.028638	0.25	0.5	0.125	0.045455	2.2	1.428571	2.2	5	0.403636
269	52.33	0.75	63.33	0.79	0.647	16		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.22969	0	0.5	0.125	0.047619	2.2	1.5	2.2	5	0.403636
270	52.33	0.75	63.33	0.79	0.647	5		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.064874	0.25	0.5	0.125	0.066667	2.2	2.142857	2.2	5	0.403636
271	52.33	0.75	63.33	0.79	0.647	14		6.51	1.873339	7284000	15.801191	0.024922	6.51	0	0.275278	0.25	0.5	0.125	1	2.2	0	2.2	5	0.403636

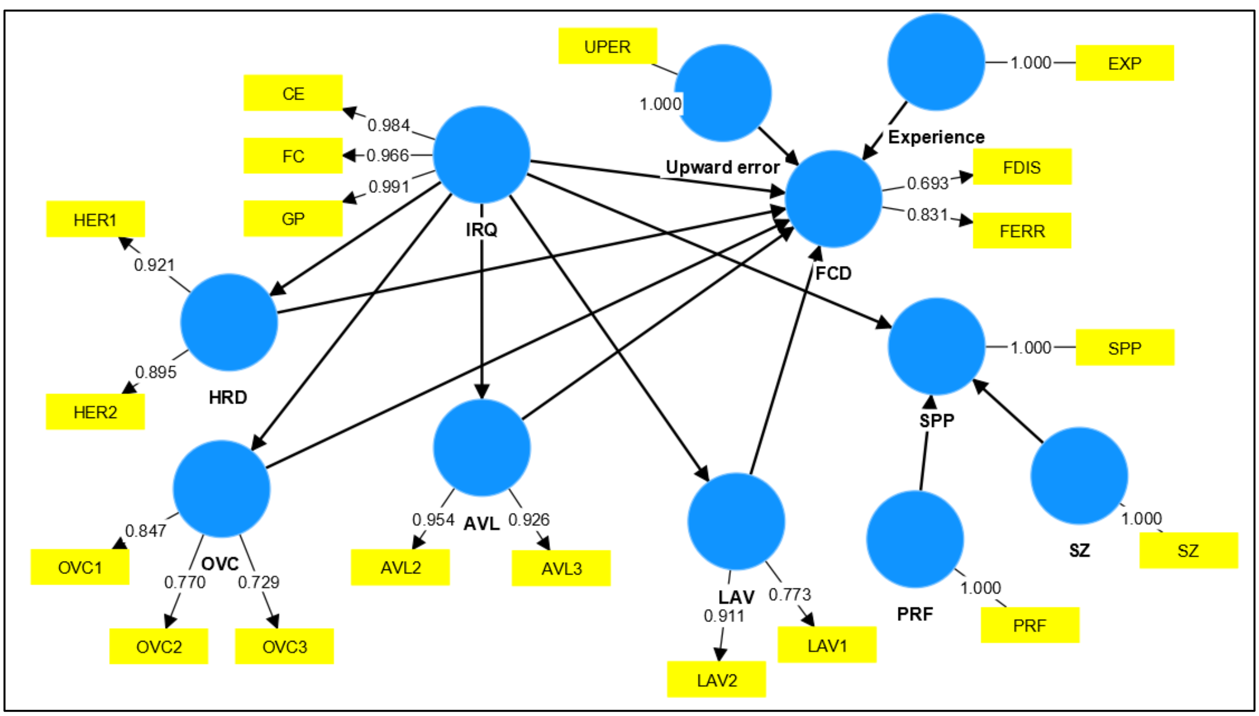
Company-level

D	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS
s prices (2), use this sheet for all formula					20.00		70.00		80.00		28.00	29.00	30.00	31.00	32.00	33.00	34.00	35.00	36.00	37.00	38.00	39.00	40.00	41.00	
CoYr	FERR	F_ERR	FDIS	F_DIS	FC_RAW	FC	GP_RAW	GP	CE_RAW	CE	UPERR	EXP	SPP	PRF	LN_PRF	TA	LN_TA	AVL1	AVL2	AVL3	OVC1	OVC1a	OVC2	OVC3	OVC4
ANH15	4.015476928	1.390156127	4.72206E-05	-9.96068136	7.3333333	0.3666667	39.33333	0.561905	51.66667	0.645833	0.484	12	-0.13766	9.26	2.225704	134635000	18.718078	0.074766	9.26	0	0.061409	0.25	0.708333	0.043478	0.028571
ANH16	61.62948151	4.121140352	0.000106089	-9.15122868	3.3333333	0.1666667	12	0.171429	14.33333	0.179167	0.568	18	-0.04626	1.69	0.524729	256586000	19.362974	0.062084	9.26	-3.6618	0.152093	0.25	0.607143	0.037037	0.033333
ANH17	3.631609407	1.289675913	5.11378E-05	-9.88098723	4	0.2	13.66667	0.195238	17.66667	0.220833	0.778	12	-0.37081	4.5	1.504077	246126000	19.321354	0.070175	1.69	-0.84523	0.004035	0	0.392857	0.035714	0.035714
ANH18	2.959512931	1.085024704	4.44204E-05	-10.021812	4	0.2	18.33333	0.261905	23	0.2875	0.676	21	0.223373	3.54	1.264127	233868000	19.270267	0.061033	4.5	-1.44939	0.251471	0.25	0.461538	0.038462	0.032258
ANH19	10.07855611	2.310410009	3.34072E-05	-10.306739	3	0.15	16	0.228571	18.66667	0.233333	0.545	5	-0.04739	5.58	1.719189	236648000	19.282084	0.080119	3.54	-1.40249	0.194128	0.25	0.62963	0.037037	0.030303
ANH20	9.850068826	2.287478443	5.64359E-05	-9.78240541	3.3333333	0.1666667	14.66667	0.209524	19.33333	0.241667	0.471	22	-0.82264	1.83	0.604316	226410000	19.237858	0.104869	5.58	0.120861	0.278515	0.5	0.642857	0.035714	0.028571
ABG15	18.52941176	2.919359295	0.000733725	-7.21737594	15	0.75	58.33333	0.833333	65	0.8125	0.357	18	0.204444	1.86	0.620576	936141000	20.657277	0.031153	1.86	0	0.023297	0	0.3	0.1	0.047619
ABG16	12.9047619	2.557596383	0.0013103	-6.63749916	15.333333	0.7666667	57.66667	0.82381	64.33333	0.804167	0.331	18	-0.19937	1.97	0.678034	918311000	20.638047	0.02439	1.86	-0.0033	0.043451	0	0.363636	0.090909	0.027778
ABG17	4.585748792	1.522953406	0.00047527	-7.65162689	14.333333	0.7166667	56.33333	0.804762	64	0.8	0.429	19	-0.52601	1.79	0.582216	988358000	20.711556	0.02005	1.97	0.032231	0.058722	0.333333	0.25	0.125	0.047619
ABG18	0.947112222	-0.05433769	0.000657859	-7.32652058	12.666667	0.6333333	53.33333	0.761905	58.66667	0.733333	0.538	19	0.984998	1.67	0.512824	1.08E+09	20.79993	0.021127	1.79	0.15841	0.206604	0.5	0.777778	0.111111	0.055556
ABG19	7.983240223	2.077344372	0.000803466	-7.12657543	14	0.7	52.33333	0.747619	57	0.7125	0.75	3	0.312106	1.55	0.438255	1.16E+09	20.871535	0.020772	1.67	-0.04673	0.074939	0.25	0.571429	0.142857	0.010417
ABG20	3.571428571	1.272965676	0.001018853	-6.88907739	15.666667	0.7833333	56	0.8	62.66667	0.783333	0.667	3	-0.44181	0.68	-0.38566	1.531E+09	21.149265	0.011236	1.55	-0.19911	0.040284	0.25	0.666667	0.333333	0.111111
AFE15	5.043855422	1.618170754	0.0007286	-7.22438499	9.6666667	0.4833333	30.66667	0.438095	37.33333	0.466667	1	15	-0.00057	8.39	2.127041	17794000	16.694372	0.006231	8.39	0	0.083877	0.25	1	0.5	1
AFE16	10.05769231	2.308337745	0	0	8.3333333	0.4166667	24	0.342857	31.66667	0.395833	1	17	-0.04876	7.26	1.98238	15820000	16.576786	0.004435	8.39	-0.02096	0	0.25	1	1	-0.00498
AFE17	9.476190476	2.248782387	0.000704761	-7.25765114	6.6666667	0.3333333	25.33333	0.361905	30	0.375	0.67	16	0.050251	8.84	2.179287	15971000	16.586285	0.007519	7.26	-0.08295	0.12234	0.25	1	0.333333	0.035714
AFE18	3.697806086	1.307739694	0.000957311	-6.95138182	6	0.3	22.33333	0.319048	27.33333	0.341667	1	12	-0.05139	6.99	1.944481	22275000	16.918976	0.011737	8.84	-0.00835	0.080193	0.25	0.6	0.4	0.142857
AFE19	3.305435145	1.195568127	0.000320538	-8.04550979	7.3333333	0.3666667	28.66667	0.409524	34.66667	0.433333	1	12	1.846464	7.95	2.073172	23133000	16.956771	0.005935	6.99	0.00899	0.206053	0.25	1	0.5	0.333333

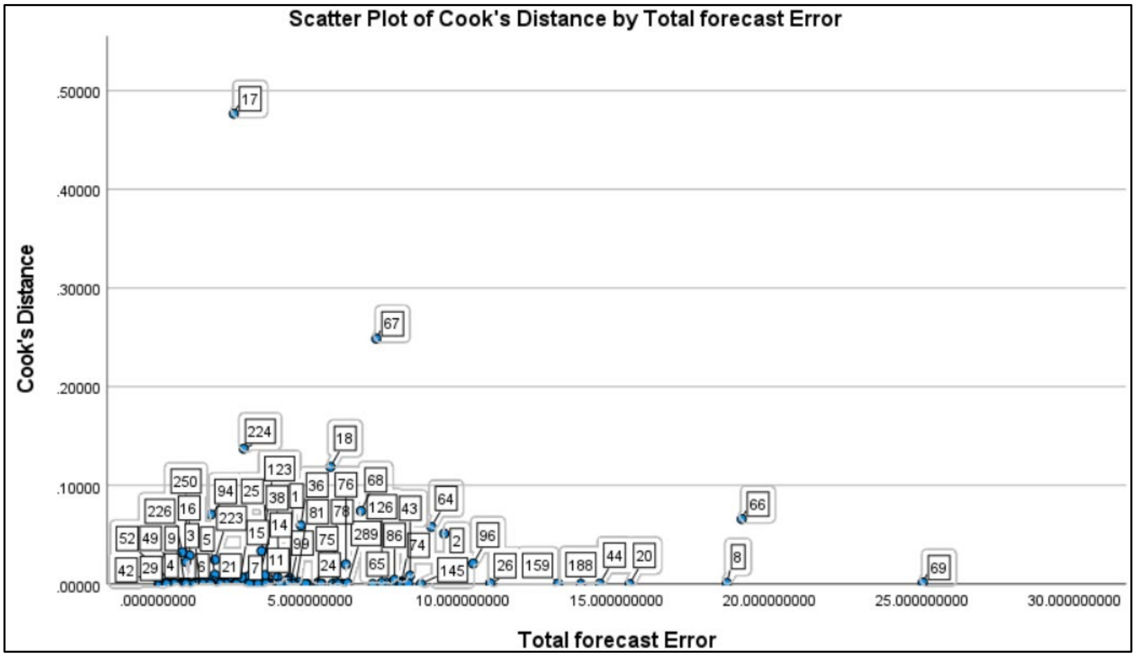
Appendix C: Measurement Model Results in SmartPLS 4



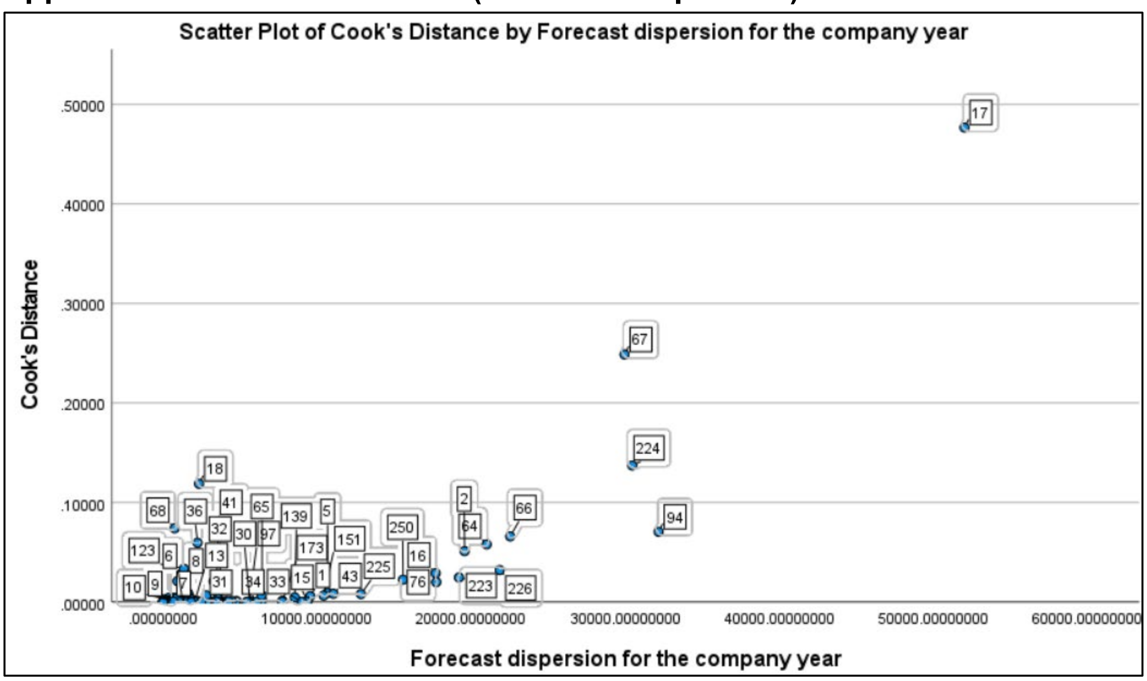
Appendix D: Final Measurement Model in SmartPLS4



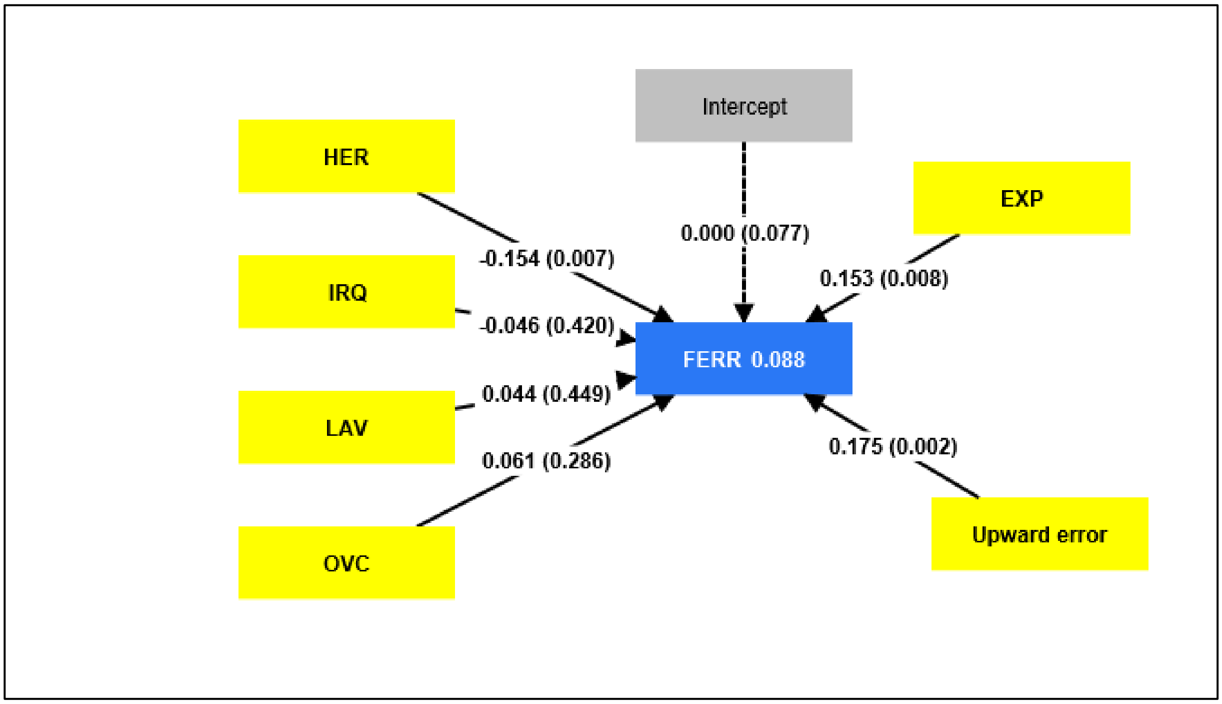
Appendix E: Cook's Distances (Forecast Error)



Appendix F: Cook's Distances (Forecast Dispersion)



Appendix G: Regression results (path diagram from SmartPLS)



Appendix H: Examples of messages used to recruit participants for the study

Part A: Example of a message sent to potential participant via email (first phase of recruitment)

Hi xxx,

It's been a while - I hope you are well! I am busy with research for a phd thesis that covers sell-side analyst research. I would like to have a short interview with you based on your experience as an analyst, for inclusion in my thesis. All data will be confidential and anonymous - I have ethics clearance from Wits (attached). I’ve also attached a participant information sheet and consent form, which we will go through when we meet.

Please let me know if you will be available for between 45 - 60 minutes sometime next week. I'll schedule an MS Teams meeting. Look forward to reconnecting!

Keep well!

Avani

Part B: Messages sent to participants via LinkedIn or Email (second phase of recruitment)

LinkedIn:

Hi xxxx. I’ve been referred to you by xxx. I am a lecturer and phd candidate at Wits. I would like to invite you to participate in a research project involving equity analysts. Please could we meet online for a few minutes to discuss the project? Avani 083*** avani.sebastian@wits.ac.za

Email:

Dear xx,

My name is Avani Sebastian. I am a lecturer at Wits and PhD (Finance) candidate. I spoke to xxx yesterday and she kindly connected us via email.

Thank you for agreeing to meet with me – I am very grateful since the forecasts of equity analysts is a key aspect of my research. I attach the following files to this email:

1. Ethics Certificate
2. Participant Information Sheet
3. Participant Consent Form

Please note that all information shared in the interview will be confidential, as per the University Ethics requirements.

Please let me know when is a suitable time to have a call on MS Teams. I am available on xxx.

Many thanks,

Appendix I: Ethics Clearance Certificate

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Research Office

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)
R14/49 Sebastian

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: H21/11/67**
PROJECT TITLE	An analysis of the impact of information quality uncertainty on decision-making and share price performance on the JSE
INVESTIGATOR(S)	Mrs A Sebastian
SCHOOL/DEPARTMENT	Accountancy/
DATE CONSIDERED	26 November 2021
DECISION OF THE COMMITTEE	Approved Risk Level: Minimal
EXPIRY DATE	19 December 2024

DATE 20 December 2021 **CHAIRPERSON** J Knight
(Professor J Knight)

cc: Supervisor : Professor Y Seetharam

DECLARATION OF INVESTIGATOR(S)

To be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10004, 10th Floor, Senate House, University. Unreported changes to the application may invalidate the clearance given by the HREC (Non-Medical)

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to submit an amendment of the protocol to the Committee. **I agree to completion of a regular progress report. For Minimal and Low studies, this is due annually on 31 December. For Medium and High Risk studies, this is due twice annually on 30 June and 31 December.**

Avani Sebastian
Signature

04 / 01 / 22
Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

Appendix J: Participant Information Sheet

WITS UNIVERSITY

PARTICIPANT INFORMATION SHEET

Research project: An analysis of the impact of information quality uncertainty on decision-making and share price performance on the JSE

Dear Sir / Madam,

My name is Avani Sebastian and I am a PhD student in Finance at the University of the Witwatersrand, Johannesburg. As part of my studies, I have to undertake a research project, and I am investigating the impact of information quality uncertainty on decision-making under the supervision of Dr Yudhvir Seetharam. The aim of this research project is to analyse the effect of financial information and decision-making on share prices of JSE-listed companies.

As part of this project, I would like to invite you to take part in an interview. This activity will involve a single online interview with myself and will take around 20 to 30 minutes. There may be a few follow-on questions, which I will communicate via email, if you are willing. With your permission, I would also like to audio record the interview using a digital device. This recording will be stored in a password protected computer and only the researcher will have access to this recording. It will be deleted after 3 years.

There will be no personal costs to you if you participate in this project. You will not receive any direct benefits from participation but there are no disadvantages or penalties if you do not choose to participate or if you withdraw from the study. You may withdraw at any time or not answer any question if you do not want to. The interview will be completely confidential and, the information you give to me will be held securely and not disclosed to anyone else. I will be using a pseudonym (false name) to represent your participation in my final research report. The report will not contain any features which will allow readers to identify the participants.

If you have any questions during or afterwards about this research, feel free to contact me on the details listed below. This study will be written up as a research report which will be available online through the university library website. If you wish to receive a summary of this report or selected findings, I will be happy to discuss and share these with you.

If you have any concerns or complaints regarding the ethical procedures of this study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za

Yours sincerely,
Mrs. Avani Sebastian (Researcher)
083 446 4055

Supervisor:
Prof. Yudhvir Seetharam (PhD, FIFM), yudhvir.seetharam@wits.ac.za, 011 717 8117

Appendix K: Participant Consent Sheet

WITS UNIVERSITY

PARTICIPANT CONSENT SHEET

<u>Research Project</u>: An Analysis of the Impact of Information Quality Uncertainty on Decision-Making and Share Price Performance on the JSE

<u>Researcher</u>: Mrs. Avani Sebastian (Supervised by Prof. Yudhvir Seetharam)

I, ..., agree to participate in this research project. I have been given a **Participant Information Sheet** which explains the nature and processes involved in this study, which is attached hereto.

Specifically, I agree to the following: (Please circle the relevant options below.)

I understand that my participation will remain anonymous.	YES	NO
I agree that the researcher may use anonymous quotes in his / her research report.	YES	NO
I agree that the interview may be audio recorded.	YES	NO
I understand that, even if I initially consent to take part in the study, I may subsequently withdraw at any time and would not be required to give any reasons; if that happened, any data collected about me for the purposes of the study would immediately be destroyed, unless I give consent for it to be retained.	YES	NO
I agree to being contacted for follow-up questions via email.	YES	NO

.... (Participant's signature)

.... (Name of participant)

.... (date)

Appendix L: Firms included in the Global Research Analyst Settlement Agreement with the Securities Exchange Commission in 2003

1. Bear, Stearns & Co. Inc. (Bear Stearns),
2. Credit Suisse First Boston LLC (CSFB),
3. Goldman, Sachs & Co. (Goldman),
4. Lehman Brothers Inc. (Lehman),
5. Merrill Lynch Incorporated (Merrill Lynch),
6. Morgan Stanley & Co. Incorporated (Morgan Stanley),
7. Citigroup Global Markets Inc.,
8. Salomon Smith Barney Inc. (SSB),
9. UBS Warburg LLC (UBS Warburg),
10. U.S. Bancorp Piper Jaffray Inc. (Piper Jaffray).

Appendix M: Main journals included in the Bibliometric Analysis

Journal	Number of publications	H-Index
JOURNAL OF ACCOUNTING & ECONOMICS	19	15
JOURNAL OF FINANCIAL ECONOMICS	16	15
ACCOUNTING REVIEW	27	13
JOURNAL OF ACCOUNTING RESEARCH	21	13
REVIEW OF ACCOUNTING STUDIES	22	13
JOURNAL OF BANKING & FINANCE	21	11
JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS	14	10
MANAGEMENT SCIENCE	13	9
REVIEW OF FINANCIAL STUDIES	8	7
JOURNAL OF BUSINESS FINANCE & ACCOUNTING	10	6
JOURNAL OF FINANCE	6	6
ACCOUNTING AND BUSINESS RESEARCH	8	5
CONTEMPORARY ACCOUNTING RESEARCH	12	5
FINANCIAL ANALYSTS JOURNAL	6	5
JOURNAL OF CORPORATE FINANCE	7	5
EUROPEAN FINANCIAL MANAGEMENT	4	4
FINANCE RESEARCH LETTERS	12	4
FINANCIAL MANAGEMENT	5	4
INTERNATIONAL REVIEW OF FINANCIAL ANALYSIS	10	4
JOURNAL OF FINANCIAL MARKETS	4	4
REVIEW OF QUANTITATIVE FINANCE AND ACCOUNTING	6	4
ACCOUNTING AND FINANCE	5	3
EUROPEAN ACCOUNTING REVIEW	5	3
JOURNAL OF BEHAVIOURAL FINANCE	9	3
PACIFIC-BASIN FINANCE JOURNAL	6	3
STRATEGIC MANAGEMENT JOURNAL	7	3
APPLIED ECONOMICS	4	2
SUSTAINABILITY	4	2

Source: Author’s own

Appendix N: Bloomberg Analyst Recommendation Scores

Recommendation	Coding	Number
hold	Hold	3
buy/attractive	Buy	4
buy	Buy	4
Speculative hold	Hold	3
Equalwt/In-Line	Hold	3
Underwt/In-Line	Sell	2
overweight	Buy	4
Overwt/In-Line	Buy	4
sell/attractive	Sell	2
Sell/Neutral	Sell	2
sell	Sell	2
neutral/neutral	Hold	3
neutral	Hold	3
outperform	Hold	3
speculative buy	Buy	4
underperform	Hold	3
reduce	Hold	3
market perform	Hold	3
add	Buy	4
underweight	Sell	2
equalweight	Hold	3
Underwt/Attractive	Sell	2
sector outperform	Hold	3
Equalwt/Attractive	Hold	3
Overwt/Attractive	Buy	4
Buy/Neutral	Buy	4
neutral/attractive	Hold	3
sector perform	Hold	3
accumulate	Hold	3
Equalwt/No Rating	Hold	3
Overwt/No Rating	Buy	4
Overwt/Cautious	Hold	3
Equalwt/Cautious	Hold	3

Source: Bloomberg (2023)

Appendix O: Conference Papers

Quantitative Analysis:

HYBRID CONFERENCE

The Southern African Finance Association's
2024 Conference

Book of Abstracts

SAFA
SOUTHERN AFRICAN FINANCE ASSOCIATION

16 – 19 January 2024

Does Quality Reduce Bias? Examining Integrated Reporting Quality on Reducing Bias in Sell-Side Analysts

– Avani Sebastian* & Yudhvir Seetharam

Background: Sell-side equity analysts rely on financial information contained in corporate reports for data for their valuation models. However, the potential for their forecasts to be affected by behavioural bias is documented in prior research. Given the purpose of corporate reports, specifically companies' integrated reports, to enable a more efficient allocation of capital, one would expect that high quality reports would reduce the likelihood of analysts resorting to heuristics in developing their recommendations.

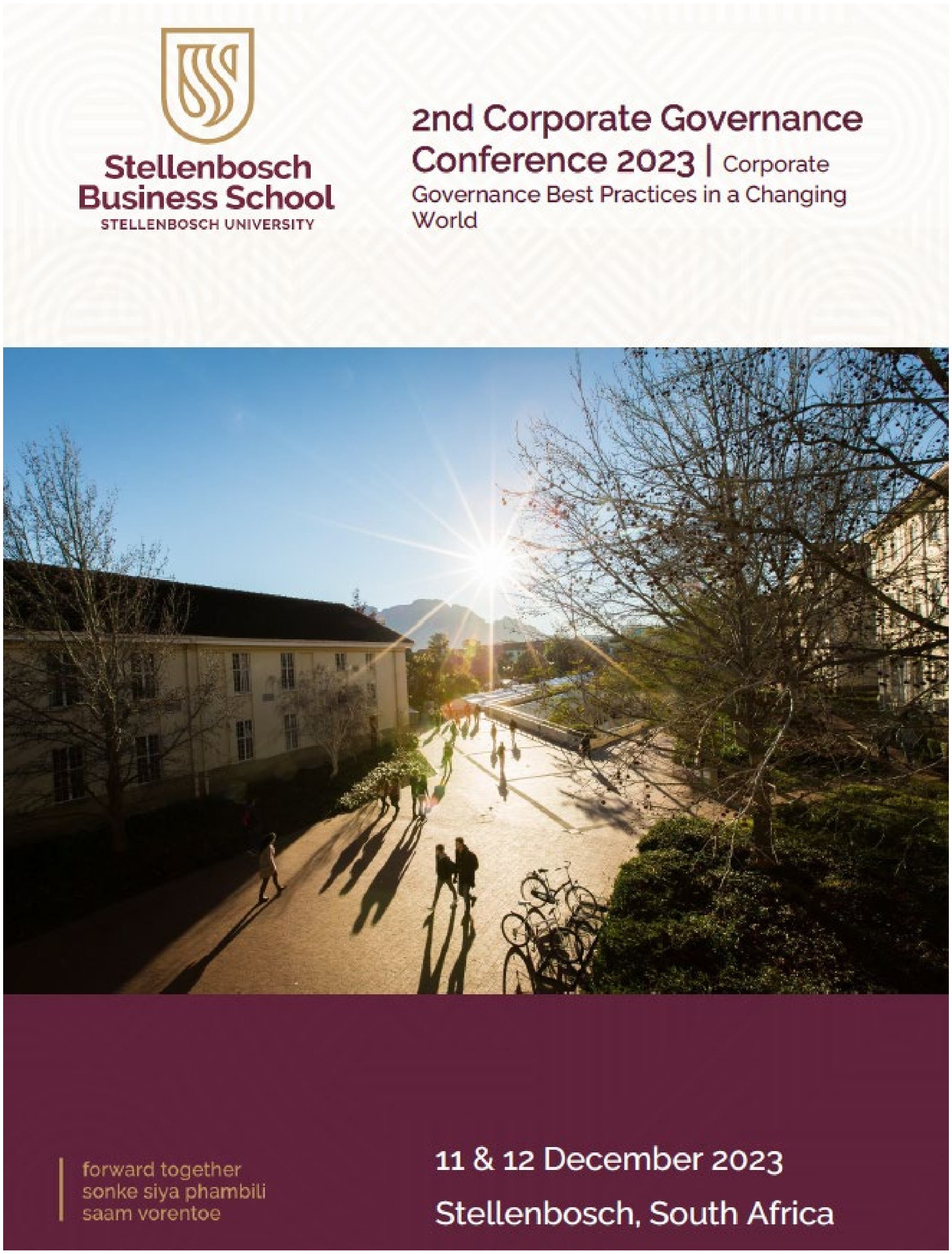
Purpose: Our aim is to determine the effect of integrated report quality on behavioural bias and analysts' share price forecasts.

Design/ Methodology/ Approach: We employ a partial least squares structural equation model, with latent variables for integrated report quality, analysts' behavioural bias and analysts' forecast quality. Our data comprises report quality scores for 342 company-years over a 6-year period until 2021. A total of 2208 recommendations are included for a 6-year period until 2021, covering 316 analysts and 60 asset management institutions. The latent variable of Forecast Decision Quality (FDQ) comprised of indicators for forecast accuracy and the dispersion of forecasts amongst analysts for each company. The latent variable of Integrated Report Quality (IRQ) comprised of scores awarded by expert adjudicators in the annual Integrated Report Quality Awards, hosted by audit firm, EY.

Findings: The relationship between IRQ and FDQ was negative and insignificant, showing a lack of reliance on integrated reports. Descriptive statistics indicate reliance on financial information from SENS trading updates instead of detailed integrated reports. IRQ showed a negative and significant relationship with loss aversion, possibly due to analysts adopting a more conservative approach when dealing with poorer quality integrated reports. Prior research suggests the tendency for analysts to issue optimistic forecasts. Our results show the upward error variable significant only at the 10% level. We conclude that deficiencies in integrated report quality are not likely to lead to increased proclivity for heuristics, although they may lead to analysts adopting a more conservative approach when issuing forecasts. Finally, the biases of availability, herding and overconfidence were found to have a significant effect on analysts' FDQ.

Contribution: This study contributes to the literature on sell-side analyst forecasts for JSE-listed companies. The context is notable as one would expect an excellent information environment for JSE-listed companies, given that the exchange is one of the few in which integrated reports are effectively mandatory. We present a novel theoretical contribution by juxtaposing behavioural bias with the information environment of the capital market.

Qualitative Analysis:



CGC23/15 Author: **Sebastian, Avani**; Seetharam, Yudhvir
Affiliation: University of the Witwatersrand
Title: **"Gut feel": Equity analysts' perceptions of executive management team dynamics and integrated reports**

Purpose: A key purpose of integrated reports is to provide useful information to providers of financial capital. Institutional investors use research reports from sell side equity analysts when making their investment decisions. In turn, the analysts' research is based on multiple sources of information, including discussions with executive management teams of the companies that they cover.

Our aim is to explore the various sources of information about company performance and how they inform analysts' investment recommendations. We sought to understand, firstly, the tangible and intangible sources of information used by analysts. Secondly, we sought to explore the relative contribution of these sources of information to the formulation of the analysts' recommendations.

Findings: Interactions with company management are the most important source of information for analysts. Trading updates are used to update analysts' financial models. Integrated reports are used occasionally to supplement other sources of information, or in preparation for meetings with management. In these meetings, analysts gathered information about the company's future prospects both directly, from questions about the company's future plans and indirectly, from perceptions about the reliability of management's assertions. One respondent aptly used the term "gut feel" to describe this phenomenon. Independence within the executive management team and the trustworthiness of management were key contributors to the perception of the company as an investment prospect. Regarding trustworthiness, the analysts kept a mental track record of whether management had executed plans that were previously discussed. Non-specific descriptions and technical jargon from management were not well-received by the analysts. However, willingness of the management team to engage with analysts and intuitional investors was viewed favourably. The analysts also evaluated the autonomy afforded to key members of the executive team. Dominant CEO's were perceived as a risk factor in the investment case for the company. Analysts observed the interactions between the CEO and other members of the executive team. Perceptions of dominance were created when the CEO fielded most of the questions in the meetings with analysts; when members of the executive team deferred to the CEO for permission to respond or for confirmation of their responses, either directly or indirectly, via gestural cues.

Design / Methodology: Semi-structured interviews were conducted with 20 practitioners who were working as, or who had worked as, sell side equity analysts. Interview transcripts were coded in two cycles, and themes were documented.

Originality: The relationship between corporate governance and financial performance is well documented. Yet, there remains a lacuna in the research on how equity analysts use corporate reports and interactions with company management to inform investment recommendations. The present research is one of the few that provide first-hand accounts of investment experts on how they gauge independence and reliability of key members of executive management.

Research limitations: Limitations: The recommendations provided by analysts to institutional investors may not necessarily be aligned to the ultimate investment decision. One of the reasons for this is that the subject company may not be aligned with the investment philosophy and mandate of the potential investor company.