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The Effect of Annual Report Complexity on Market Reaction: An Analysis Using ChatGPT

Dhiki Mulyadi[1], Ani Wilujeng Suryani[2*], Hazreel Hasmi[3], Yongky Teguh Setiaji[4]
[1,2,4]Universitas Negeri Malang, Jl. Semarang No. 5, Malang, Indonesia
[3]Le Cordon Bleu, Adelaide, Days Road, Regency Park, Adelaide, Australia

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Correspondence:
*ani.suryani@um.ac.id

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Abstract
Purpose: The purpose of this study is to examine the effect of annual report complexity on market reactions.
Method: The sample consists of 587 annual reports from companies listed on the Indonesia Stock Exchange (IDX) in 2023. The complexity scores, which become the independent variable, were assessed from Management Discussion and Analysis section using pre-trained ChatGPT-4. For the dependent variable, we used the market model to identify abnormal returns. Finally, regression was performed to investigate the impact of complexity on the abnormal returns.
Findings: We found that the complexity has a positive impact on the abnormal returns. This indicates that more complex annual reports are associated with an increase in abnormal returns, and managers utilized strategic narratives and complex report structures to shape positive perceptions of the company.
Originality/Value: To the researchers' knowledge, no previous research has explored the utility of artificial intelligence (AI) tools like ChatGPT in conducting textual analysis of annual reports of in Indonesia. The findings also demonstrate how AI-based tools can enhance capital market text analytics and support financial disclosure analysis in emerging markets.
Keywords: AI; ChatGPT; Textual Analysis; Annual Report; Readibility; Market Reaction
Paper Type: Research Paper.

1. Introduction

Corporate annual reports have become increasingly complex over the past two decades. Evidence shows that between 1995 and 2017, the complexity of annual reports increased by more than 100%, as indicated by longer report lengths and more extensive textual disclosures (Cohen et al., 2020; Dyer et al., 2017). Complexity refers to the level of difficulty involved in reading and understanding a text (Frankel et al., 2022). The use of complex language in corporate reports can reduce readability and limit the informational value provided to stakeholders (Toit, 2017). When annual reports become more difficult to read, investors must spend additional time and resources to process the information, which increases the risk of misinterpretation and poor investment decisions (Babu & Hossain, 2019; Hales, 2007; Phuong & Huong, 2022). Prior studies also suggest that low readability may negatively affect market outcomes, including reduced stock liquidity and weaker investor responses, because complex disclosures hinder investors' ability to process corporate information efficiently (Boubaker et al., 2019).

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The increasing complexity of annual reports is also evident in the Indonesian context. Corporate annual reports have become longer and more detailed as companies comply with extensive disclosure requirements issued by regulators. For example, regulations issued by Otoritas Jasa Keuangan (Indonesia Financial Services Authority) require public companies to disclose various elements such as corporate governance reports, management discussion and analysis (MD&A), sustainability information, and reports from supporting committees, as stipulated in POJK No. 29/POJK.04/2016 concerning annual reports of public companies. These requirements significantly increase the amount of narrative information presented in annual reports and may create a greater information-processing burden for investors. In addition, the adoption of International Financial Reporting Standards (IFRS) has further expanded disclosure requirements and encouraged companies to provide more detailed qualitative explanations in financial reporting. Prior studies on Indonesian listed companies show that after the adoption of IFRS, the readability of financial disclosures declined, indicating that the reports became more difficult to understand (Hidayatullah & Setyaningrum, 2019). Furthermore, disclosure length increased from approximately 20,250 words before IFRS adoption to 24,189 words after adoption, reflecting a substantial growth in the volume of information that investors must process when evaluating corporate reports. These developments suggest that the reporting environment in Indonesia has evolved toward more complex disclosure structures, which may affect how investors interpret information contained in annual reports.

From a theoretical perspective, the readability of annual reports plays an important role in shaping how investors interpret corporate information. Prior research suggests that complex disclosures may be used strategically by managers to obscure unfavorable information or hide poor performance (Xu et al., 2019). Consistent with this view, several studies find that higher disclosure complexity is associated with weaker market reactions and lower stock prices because investors face greater difficulty understanding the information presented (Alduais et al., 2022; Lee, 2012; Xu et al., 2019). Reports that are difficult to read may confuse investors and reduce market confidence, thereby discouraging investment (Lim et al., 2018). Conversely, clear and easy-to-read reports can enhance transparency and improve investors' perceptions of a company, which may lead to stronger investor support and more favorable market responses (Dau et al., 2024).

These issues are particularly relevant from the perspective of the efficient market hypothesis, which states that stock prices reflect all available information in the market (Fama, 1970). Annual reports are among the most important channels through which firms communicate financial and non-financial information to investors and other stakeholders (Ertugrul et al., 2017). By providing comprehensive information about corporate performance, annual reports serve as a key resource for monitoring managerial actions and supporting investment decision-making (Luo et al., 2018). However, as disclosure complexity increases, investors may face difficulties in interpreting the information contained in these reports (You & Zhang, 2009). As a result, complex disclosures can slow the information absorption in the market and potentially hinder the ability of stock prices to reflect information efficiently (Liu & Liu, 2021). This suggests that disclosure complexity may act as a barrier to market efficiency.

Studies on readability have primarily focused on texts written in English and originating from developed nations such as the United States and the United Kingdom (de Souza et al., 2019). This study aims to expand the scope of research to developing economies where English is not the primary language. In Indonesia, annual reports are published in both Indonesian and English. Prior studies have emphasized the need to develop a more precise readability metric for the Indonesian language (Adhariani & Toit, 2020). Therefore, this study aims to measure the readability of annual reports in Indonesian using ChatGPT. ChatGPT was chosen because it allows investors to work in multiple languages and has the potential to eliminate the dominance of English (Ghio, 2024). The ability to work in multiple languages enables ChatGPT to analyze and measure the readability of annual reports presented in Indonesian.

However, despite its advantages, ChatGPT's textual analysis is often prone to errors, unreliable, and sometimes unable to make logical inferences (Floridi, 2023). ChatGPT also has the potential to generate biased responses, lack emotional intelligence, and be limited by the knowledge obtained from training data (Kalla & Kuraku, 2023). However, these weaknesses can be mitigated through prompt design to optimize ChatGPT's use. A prompt is a sentence or phrase added to an AI model to help activate it and trigger a specific response to a task (Ding et al., 2021). Prompt design is defined as the process of formulating concise, clear, and specific sentences. The objective of this process is to provide the model with sufficient information to produce the desired output (Ahmed et al., 2024). For example, a two-step prompt framework was utilized to derive sentiment scores from extracted textual data (Lefort et al., 2024). Sentiment scores derived from two-step prompts have proven effective in predicting short- and medium-term movements in equity markets.

One of the informational resource investors use to inform their choices is annual reports. In Indonesia, annual reports are the most frequently accessed publications by investors, including retail investors and securities companies (IDX, 2022). The high level of access to annual reports reflects the important role of these documents in conveying information about a company's performance and prospects. However, if the reports presented by companies are difficult to read, investors will find it difficult to extract the information contained therein (Toit, 2017). This can hinder understanding of the company's actual condition and ultimately affect the quality of investment decisions (Xu et al., 2019). Previous research shows that report complexity can reduce readability and obscure the message conveyed (Li, 2008), thereby impacting market efficiency (Lee, 2012). Annual reports are important for investors in Indonesia because they contain strategic explanations and qualitative information not found in financial statements, thereby helping to understand the company's performance and prospects more comprehensively (Indrayani & Chariri, 2014). This makes annual reports in Indonesia important to study, especially in relation to the complexity of the reports produced by companies.

The advent of predictive artificial intelligence (AI) technologies like Chat-GPT has created significant opportunities for processing textual data (Kok, 2024), including the analysis of textual content in annual reports (Bilinski, 2024). With the advancement of technology, ChatGPT has become a potential tool to analyze financial text more efficiently and accurately (Bhaskar et al., 2023). ChatGPT can help summarize complex annual report disclosures so that the information presented becomes shorter, but still informative, and can assist investors in making better decisions (Kim et al., 2023a). ChatGPT is a transformer-based system trained on a large corpus of text data (Large Language Models - LLM) specifically designed to generate human-like text (Giordano et al., 2024). LLMs are AI models that have been trained on vast amounts of text to produce language output similar to that of a human (Hadi et al., 2024). Transformer is an artificial intelligence model designed to process and interpret sequences of data using attention mechanisms (Vaswani et al., 2017). Transformer architectures with attention mechanisms can detect the connections among words, sentences, and paragraphs within textual documents (Kim et al., 2023b). ChatGPT is designed on the basis of transformers and has the ability to analyze text by considering context and relationships between words, thus enabling more accurate assessment of text complexity and sentiment (Brown et al., 2024; Vaswani et al., 2017).

The role of generative AI tools such as ChatGPT in enhancing investors' ability to process information has been investigated in prior research. Generative AI has the potential to improve the way investors process information, especially for stakeholders with limitations in analyzing information (Kim et al., 2023a). Previous research has shown that large language models (LLMs) such as ChatGPT can perform financial statement analysis comparable to that of professional financial analysts (Kim et al., 2024). LLMs can accurately predict future profits beyond the capabilities of human financial analysts. When faced with large or complex data, human analysts may overlook patterns and trends that LLMs can identify. Additionally, artificial intelligence (AI) can process data much more efficiently in terms of time and cost than human analysts (Dong, 2024). Previous research shows that ChatGPT can be used for market research (Brand et al., 2023), help evaluate financial information (Pelster & Val, 2024), and predict stock price volatility (Kim et al., 2023b). This indicates that ChatGPT has potential to be used in the textual analysis of annual reports.

A previous study has utilized ChatGPT to derive sentiment scores from Bloomberg market summaries, with results indicating that the generated values exhibit strong predictive capabilities regarding market reactions (Lefort et al., 2024). ChatGPT has also successfully measured investment scores from public exposure transcripts, enabling it to predict future capital expenditures and provide additional information about a company's future investment opportunities (Jha et al., 2023). Thus, ChatGPT can be used for textual content analysis and converted into a simple score to assist investors in their decision-making. Therefore, this study aims to use ChatGPT to generate a useful complexity score for annual reports for investors. This study will use ChatGPT to obtain a complexity score from annual reports. The influence of the complexity score generated by ChatGPT on market reactions during annual report announcements will be examined using a regression analysis.

This study aims to analyze the impact of annual report complexity on market reactions in the Indonesian capital market by utilizing artificial intelligence (AI), specifically ChatGPT, to evaluate the complexity of corporate disclosure texts. This study makes several contributions. From a theoretical perspective, it expands the literature on financial disclosure and text analysis by exploring the role of AI in measuring the complexity of annual reports in a non-English context. From an empirical perspective, it provides new evidence on how the complexity of annual reports affects market reactions in developing countries, particularly Indonesia. From a practical perspective, this study introduces an automated approach to analyzing the complexity of annual report texts, which can help capital market participants evaluate corporate disclosures more efficiently while reducing the time and costs required for manual analysis. In addition, these findings can provide useful insights for companies and regulators in improving the clarity, transparency, and quality of communication in corporate reporting.

2. Literature Review

The efficient market hypothesis proposes that stock prices are heavily shaped by the available information (Fama, 1970). Fama (1970) categorizes market efficiency into three types: weak, semi-strong, and strong. The weak form indicates that prices reflect only historical data, while the semi-strong form incorporates all publicly available information. The strong form also considers private, insider information. In the semi-strong form, security prices incorporate all publicly available information, including firms' annual reports

(Fama, 1970). For investors, these reports serve as the main and most economical means of obtaining company-related information (Phuong & Huong, 2022). The information contained in annual reports can support investors in making decisions and managing investments (Chircop et al., 2024; Saleh & Alghusain, 2018). Information relevant to assessing a company's current performance and forecasting its future prospects can be extracted through text analysis of the narrative sections of annual reports (Sai et al., 2019).

The increasing complexity of annual reports (Cohen et al., 2020; Dyer et al., 2017) can hinder readability and reduce the value of information for investors (Toit, 2017). The complexity of annual reports can influence market efficiency, particularly under semi-strong form (Lee, 2012). Difficult-to-read information can delay investors' analysis of it, leading to market inefficiency (Lee, 2012). Difficult-to-understand information causes delays in market reactions, resulting in prices reflected in the market that are not accurate (Innocenti et al., 2012). Stock prices that do not reflect fundamental information make it difficult for investors to assess the risks and potential returns of an investment. Difficult-to-understand information triggers differences in views among analysts and increases bias in estimates, so that stock prices do not fully reflect the fundamentals of the company (Scherbina, 2003). This condition can cause investors to suffer financial losses.

In this study, annual report complexity is primarily conceptualized as linguistic difficulty, referring to the extent to which textual disclosures are difficult to read and process by investors. This definition is consistent with prior readability literature, which focuses on surface-level textual features such as sentence length and word complexity (Li, 2008). However, this study extends the conventional approach by incorporating semantic and contextual dimensions of text through the use of ChatGPT, allowing for a more comprehensive assessment of complexity beyond purely linguistic features.

Complex annual reports can make it harder for the market to react to new information. Companies with complex disclosures (longer and harder to read) are more likely to have problems with information asymmetry (Rjiba et al., 2021). Managers often write annual reports in a way that makes their company's poor performance and bad news less obvious to investors (Lo et al., 2017). Companies are motivated to obscure negative information by employing complicated wording and excessively lengthy sentences (de Souza et al., 2019; Dyer et al., 2016). It's possible to share good news with investors in a simple, clear, and easy-to-understand way but managers often choose to share this kind of bad news in a confusing, complex, and difficult-to-understand way to delay the impact of bad news on stock prices (Li, 2008). This intentionality adds complexity to narrative accounting disclosures to hide information about poor performance (de Souza et al., 2019). Therefore, investors often find it difficult to distinguish between relevant and irrelevant information. Documents that are difficult to read require greater cognitive effort to understand, thereby hindering the efficient search and extraction of useful information (Lee, 2012). Low readability can increase market uncertainty and encourage the emergence of accrual anomalies, which is a condition where the market fails to predict or reflect accrual information in stock prices, ultimately causing market inefficiency (Liu & Liu, 2021). For example, if annual reports use technical terms or overly complex sentence structures, investors may fail to pick up on negative signals that reflect a decline in company performance. As a result, stock prices remain stable or even rise, even though the company's financial condition is deteriorating.

From a theoretical perspective, the impact of disclosure complexity can be explained through the concept of investor cognitive load and information processing constraints. Complex disclosures increase the cognitive effort required to extract relevant information, thereby raising processing costs for investors (Li, 2008). According to

Bloomfield (2008), investors have limited attention and processing capacity, implying that more complex and less readable disclosures reduce the efficiency with which information is incorporated into stock prices. Furthermore, disclosure characteristics such as readability influence how effectively investors and analysts interpret firm performance and respond to new information (Bushee et al., 2018). As a result, higher disclosure complexity can slow down information processing, delay market reactions, and ultimately weaken price efficiency.

Previous research have indicated that low readability in annual reports can impair investors' information processing, which in turn diminishes trading interest and leads to reduced stock liquidity (Boubaker et al., 2019). Annual reports with low readability are associated with less stable earnings and weaker market responses to information (Xu et al., 2019). In addition, high complexity in annual reports can create ambiguity, which is the lack of clarity in the meaning of information due to the use of complex language and confusing narrative structures, making it difficult for investors to accurately and timely understand the company's condition. This ambiguity can slow down information processing and hinder investment decisions because investors need more time and cognitive effort to interpret the report's content (Li, 2008). This can result in increased stock price volatility because of the uncertainty brought on by a lack of knowledge about the company. Conversely, better readability reduces information asymmetry and strengthens investor confidence, thereby impacting stock price stability and liquidity (Gangadharan & Padmakumari, 2023). Consequently, it can be said that one significant element influencing investor behavior and market efficiency is the readability of annual reports.

The measurement of textual complexity in annual reports generally uses readability indices such as the Fog Index (Li, 2008), the Flesch Reading Ease (Courtis, 1995), and the Flesch-Kincaid Indices (Hassan et al., 2019) to assess the level of difficulty of a text. These three readability indices have been widely applied, but there are limitations to their use. These methods are performed manually (Rahman, 2014) or semi-automatically using software tools (Alduais et al., 2022; Toit, 2017), which require time and precision, especially when applied to long documents such as annual reports. Furthermore, the Flesch Reading Ease and Fog Index have limitations when applied to texts with technical terms, as they only measure sentence length and the frequency of difficult words without considering the broader semantic context (Lenzner, 2014). Although readability measures can provide a general overview of text complexity, they often fail to capture deeper semantic and contextual aspects of textual complexity (Štajner et al., 2012). Readability measures only assess surface-level aspects, such as sentence length, and are less effective at capturing sentence meaning relevant to context, particularly in texts with specific purposes. Additionally, readability measures are only effective in English, making them less relevant for assessing the readability of texts in non-English languages (de Souza et al., 2019).

To address limitations in readability, the natural language processing (NLP) approach offers a more sophisticated solution. NLP is the study of how computers and human language interact with the aim of enabling computers to understand, interpret, and generate human-like language (Mishra & Kumar, 2020). NLP transforms machines into human-like entities and facilitates human communication with machines (Sanadi & Bhat, 2022). NLP has demonstrated advantages in handling text analysis tasks, such as semantic search, translation, and sentiment analysis (Abro et al., 2023). NLP is a cornerstone of modern artificial intelligence (AI), enabling computers to process human language automatically (Dande & Pund, 2023).

One of the Artificial Intelligence (AI) tools designed with NLP is ChatGPT. ChatGPT is a sophisticated natural language processing model developed to produce human-like text in response to specific prompts or instructions (Pelster & Val, 2024). ChatGPT is an advanced language model with a transformer architecture and extensive training data, making it superior in various language-based tasks, such as translation, summarization, and question answering (Zaremba & Demir, 2023). With its transformer-based architecture, ChatGPT has the ability to analyze text by considering context and word relationships, enabling more accurate assessment of textual complexity by incorporating contextual meaning and word relationships (Brown et al., 2024; Vaswani et al., 2017). ChatGPT has the potential to enhance efficiency, productivity, and decision-making quality through fast/automated responses and data analysis (Jusman et al., 2023).

ChatGPT can also be used in various languages, enabling investors to conduct textual analysis of annual reports in non-English languages (Ghio, 2024). In Indonesia, English is not the primary language, so it is important for local investors to understand the complexities of annual reports in Indonesian from the companies being analyzed. Based on available data, the proportion of local investors in Indonesia is recorded at 56.96%, indicating dominance compared to foreign investors, who account for 43.04% (KSEI, 2024). This indicates that the Indonesian capital market is still dominated by local investor participation. Research related to readability in Indonesia has been conducted using manual techniques to measure the complexity of English-language reports (Adhariani & Toit, 2020). Similar studies have also been conducted manually in other countries, such as India (Toit, 2017), China (Alduais et al., 2022), and Malaysia (Rahman, 2014). Unlike previous studies, this study will use an automated AI tool, ChatGPT, to measure the complexity of annual reports in Indonesian.

Earlier studies have examined ChatGPT's capabilities in analyzing textual data. One application involved using ChatGPT to forecast stock market trends by evaluating sentiment in news headlines (Lopez-Lira & Tang, 2023). The results show that the sentiment scores generated by ChatGPT can predict daily stock returns, replacing traditional methods, and have stronger predictive power among smaller stocks and those following negative news. ChatGPT has also successfully obtained investment scores from transcripts of earnings conference calls, where the scores generated can predict future capital expenditures and provide additional information about a company's future investment opportunities (Jha et al., 2023). By considering the changes anticipated by managers in capital expenditures based on earnings conference call transcripts, investment scores can predict a company's future capital expenditures. Furthermore, ChatGPT can be used to summarize complex company disclosures into informative summaries that investors can use for more efficient decision-making (Kim et al., 2023a). ChatGPT has also been successfully used to help investors select stocks by providing rankings and identifying stocks that outperform (Pelster & Val, 2024). In the Indonesian context, ChatGPT has been used to summarize news articles (Khasanah & Hayaty, 2023), conduct sentiment analysis (Mardiah et al., 2024), and translate texts (Arti et al., 2025). The use of ChatGPT is also widespread in educational research fields such as biology (Haidir et al., 2024), language (Alatas et al., 2024), and psychology (Assegaf et al., 2024). Although research on ChatGPT has been extensively conducted in Indonesia, there are still few studies that utilize it for analysis in the field of economics, particularly in the context of capital markets such as the analysis of company annual reports.

ChatGPT can analyze news content and condense its assessment into a straightforward numerical score (Pelster & Val, 2024). For example, ChatGPT can be used to obtain investment scores (Jha et al., 2023) and sentiment scores (Lefort et al., 2024; Lopez-Lira & Tang, 2023). Based on this literature, this study aims to use ChatGPT to generate complexity scores from Indonesian annual reports. To test whether the complexity scores generated by ChatGPT can be used by investors in making decisions, this study will examine market reactions to the complexity of annual reports (Loughran & McDonald, 2011).

Prior research has identified an inverse relationship between the complexity of annual report disclosures and market responses (Alduais et al., 2022; Lee, 2012; Xu et al., 2019). Firms with high report complexity are associated with lower market returns because more difficult-to-read disclosures reduce investors' ability to process new information in a timely manner (Alduais et al., 2022; Lee, 2012). Investors faced with low-readability reports take longer to update their forecasts after annual information is published and produce less accurate predictions (Xu et al., 2019). Conversely, companies with high readability correlate with higher stock returns and have a positive impact on future return expectations (Alduais et al., 2022). This is because companies with good performance tend to use brief explanations to describe their operational and financial conditions, thereby reducing the complexity of their reports. Improved readability of company reports can increase information efficiency in the capital market (Hesarzadeh & Rajabalizadeh, 2019). More readable annual reports can reduce information asymmetry and strengthen investor confidence and increase company value (Bai et al., 2019; Hwang & Kim, 2017). Stock returns will be higher when annual reports are easier to read because they improve information efficiency and transparency (Gangadharan & Padmakumari, 2023). Conversely, complex annual reports can hinder market reactions and result in market inefficiency (Liu & Liu, 2021). Based on the efficient market hypothesis, relevant information in annual reports should be immediately reflected in stock prices if the market reacts efficiently (Fama, 1970). However, the complexity of annual reports can hinder investors' interpretation of information, resulting in slower or negative market reactions (You & Zhang, 2009).

Overall, the literature suggests that the complexity of annual reports plays a critical role in shaping how investors process and respond to corporate information. From the perspective of the efficient market hypothesis, relevant information should be rapidly incorporated into stock prices. However, when disclosures are complex and difficult to read, they increase investors' cognitive load and processing costs, limiting their ability to efficiently interpret available information. This can delay the incorporation of information into prices, weaken market reactions, and reduce price efficiency. Empirical evidence further indicates that firms with more complex disclosures tend to experience lower market responsiveness due to reduced information accessibility and increased uncertainty. Therefore, higher annual report complexity is expected to negatively affect market reactions. Thus, the hypothesis formulated in this study is as follows:

H_1: Annual report complexity negatively affects market reaction.

3. Research Method

3.1. Research Approach

This study utilizes the capabilities of the artificial intelligence (AI) tool ChatGPT-4 in conducting textual analysis of annual reports. The use of ChatGPT in this study was chosen for three reasons (Jha et al., 2023). First, ChatGPT offers consistent evaluations by avoiding reliance on external contemporary information or subjective opinions, thereby ensuring that its assessments of textual content remain objective and reliable. Second, due to the extensive length of annual reports, manual analysis often struggles to consistently yield accurate results in reading comprehension tasks. Third, ChatGPT is an algorithm that can process a large amount of text quickly and without significant capacity limitations. In this study, the textual analysis was conducted using GPT-4, with the model configuration set to temperature = 0 to ensure deterministic and consistent outputs across repeated queries. The temperature parameter controls the degree of randomness in the model's text generation process. A value of 0 minimizes randomness and forces the model to select the most probable response for a given prompt, which reduces variability in outputs when the same input is processed multiple times. This configuration is commonly used in research settings because it produces more stable and reproducible results, thereby improving the reliability and replicability of the textual analysis.

3.2. Data

All companies listed on the Indonesia Stock Exchange (IDX) in 2023 that released annual reports made up the study's sample. Companies included in the special monitoring list were excluded from the sample, as they had experienced a temporary suspension of securities trading by the IDX lasting more than one trading day. Additionally, companies under special monitoring were in a state of low liquidity and trading volume. This study uses corporate data from 2023 in order to prevent the effects of the COVID-19 epidemic and the 2024 elections on the research findings. Table 1 displays the number of samples in this study.

Table 1. Sample Criteria

Criteria	Total
Companies listed on the IDX	938
Companies under special monitoring	(232)
Companies that do not publish annual reports	(40)
Documents cannot be read by ChatGPT	(15)
IPO Company	(29)
Companies that issue reports coinciding with corporate actions	(35)
Total Sample	**587**

3.3. Variables, Measurement, and Data Analysis

The independent variable in this study is complexity. The complexity of annual reports was measured using ChatGPT. In this study, ChatGPT was asked to assess the complexity of the Management Discussion and Analysis (MD&A) section of Indonesian-language annual reports. The MD&A section was separated from the annual reports being analyzed and then uploaded to ChatGPT in a machine-readable format (pdf). The analysis focuses on the MD&A section because this section contains narrative explanations provided directly by management regarding firm performance, risks, and future prospects. Prior literature suggests that narrative disclosures play an important role in shaping investors' understanding of corporate information because they provide qualitative context that complements financial statements (Davis & Tama-Sweet, 2012). Therefore, analyzing the MD&A section allows the study to capture the linguistic characteristics and complexity of managerial communication in annual reports. In the MD&A, managers can manipulate disclosures to cover up poor company performance (Lo et al., 2017). Previous research shows that investors tend to focus more on reading the narrative section of the MD&A than other sections of the annual report (Dyer et al., 2017). The tone and style of language in the MD&A can influence investment decisions (Huang et al., 2014). In addition, previous studies also show that the MD&A is the most difficult part of the annual report to understand, and in some cases, this complexity is intentional on the part of management as an attempt to obscure negative information or confuse readers (Lehavy et al., 2011). Therefore, measuring the complexity of the MD&A is important because this section can be a source of information for investors in making decisions.

Before measuring the complexity of annual reports, we first trained ChatGPT's ability to perform textual analysis in Indonesian. This was done because ChatGPT is a tool designed with Natural Language Processing (NLP). Since NLP is a study conducted in English, the researcher trained ChatGPT to perform textual analysis in Indonesian. ChatGPT was instructed to compute the average number of words per sentence. Word and sentence length are the two common components on which the majority of readability formulae are based (Adhariani & Toit, 2020). The results showed that ChatGPT produces the same output as the manually calculated output. This demonstrates ChatGPT's accuracy in determining a sentence's average word count.

To get the complexity score, the researcher first asked ChatGPT to identify how it measures complexity in Indonesian. It was found that in measuring complexity, ChatGPT considers aspects of complexity based on computational algorithms and natural language processing. These aspects include lexical complexity, syntax, semantics, cohesion and coherence, contextual relevance and appropriateness, pragmatic aspects, ambiguity, and uncertainty (Bilinski, 2024). The following were the commands/prompts used to obtain the complexity score of the MD&A section in the annual reports:

1. Assume you are an Indonesian language expert who understands the complexity of Indonesian texts. What do you think is the definition of complexity?
2. How do you measure the complexity of a text? What are the considerations in measuring text complexity in Indonesian?
3. Assume you are an experienced investor. You will analyze the text complexity of the annual report in the MD&A section as a basis for making investment decisions. The following is an MD&A document of a company that you will analyze. In this document, the MD&A is presented in two languages, English and Indonesian. Analyze the complexity of the report presented in Indonesian by considering the complexity measures you have described earlier. Based on your analysis, what is the level of complexity of the MD&A in this report? Would you be interested in investing in the company?
4. Based on your analysis, give a complexity score for the MD&A section presented in Bahasa Indonesia of this report on a scale of 1 to 10, where a score of 1 indicates a very low level of complexity (simple and easy to understand), and a score of 10 indicates a very high level of complexity (difficult to understand). Include a brief explanation for the score you gave (Bilinski, 2024).

Building on previous research, this study decomposes the commands into simpler tasks and designs prompts to elaborate the objectives, focusing on specifically indicated tasks to align with ChatGPT's capabilities (Lefort et al., 2024). These prompts described the ChatGPT's position or role in a command to make the answer more specific. The assignment of commands was done using a two-step method (Lefort et al., 2024). The two-step method is a method that provides two commands to improve ChatGPT's performance in performing textual analysis. The first command (command 3) in this method aimed to extract information from the text, and the second command (command 4) converted it into a simple score. The two-step method was chosen because it is flexible and more optimal for performing predictions in a user-defined context (Lopez-Lira & Tang, 2023). This allows for more optimal use of ChatGPT in different types of prediction tasks by customizing the stages according to specific needs. The two-step prompt process is shown in Figure 1.

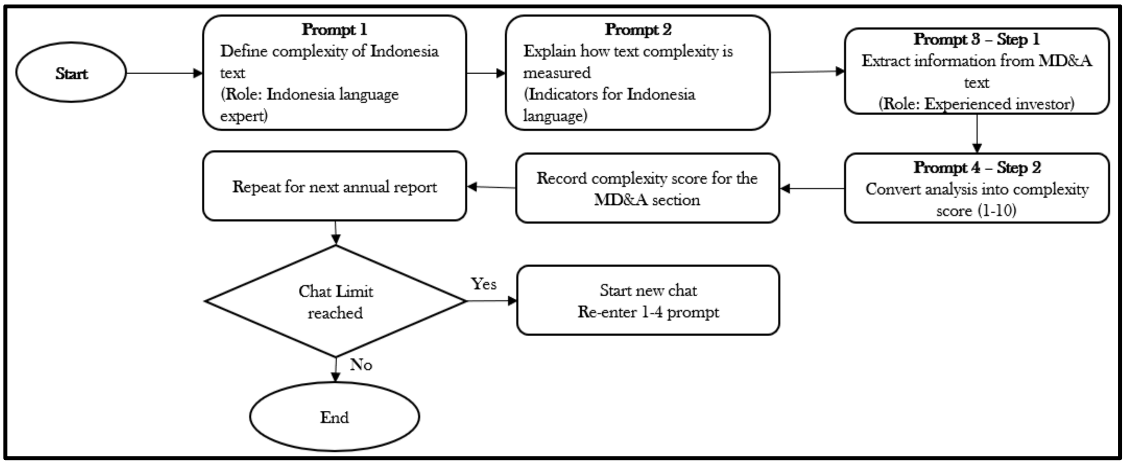

Figure 1. Two-Step Prompt Process

In addition, this study considers ethical and transparency aspects in the use of AI-assisted analysis. ChatGPT is used as a tool to support textual analysis rather than replace researcher judgment. To ensure transparency and reproducibility, the prompts and procedures used in this study are structured and consistently applied across all observations. The analysis relies solely on the textual content provided, without incorporating external or real-time information. Furthermore, the interpretation of results remains under the control of the researchers, ensuring that conclusions are drawn based on theoretical and empirical considerations.

ChatGPT's output consists of simple scores for each aspect of complexity, including readability level, number of compound sentences, vocabulary and terminology, ambiguity and double meanings, cohesion and coherence, sentence structure diversity, alignment with the target audience, text length, and the overall average score. To examine whether these scores are useful for investors, the researchers tested the average scores generated by ChatGPT against market reactions. Specifically, a regression analysis was conducted between the average scores and the Cumulative Abnormal Return (CAR) at the time of annual report publication, in order to determine whether a market reaction occurred in response to the new information. The use of Abnormal Return (AR) as an indicator of market reaction is considered more appropriate than actual stock prices or raw returns because it isolates the impact of a specific event from other market factors (Fama, 1998; Kothari & Warner, 2007). Unlike stock prices, which may be influenced by various external factors, AR reflects the difference between actual returns and expected returns, thus providing a more accurate measurement of investor responses to the information disclosed in annual reports (Li, 2008).

The market reaction, serving as the dependent variable in this study, was assessed using the event study methodology. The impact of economic events on firm value can be measured through an event study, which analyzes security price fluctuations around the occurrence of such events (Mackinlay, 1997). This approach assumes market rationality, where the effects of events are immediately reflected in stock prices (Mackinlay, 1997). Event studies track the market price of securities within an event window to detect market-related reactions and assess information content. The events in this study was the publication day of the annual report obtained from the Indonesia Stock Exchange data. In each event, the window used is 3 days before to 3 days after the event occurs. The use of a 7-day window period refers to a previous study (Bilinski, 2024) which aims to accurately capture the impact of events and avoid the impact of other events (Friedman & Singh, 1989). After the window period was decided, the estimation period was calculated. The estimation period used was 100 days before the event window (Suryani & Pertiwi, 2021).

The subsequent step involved calculating the AR, which was derived by subtracting the expected return from the actual return. To calculate the AR, the initial step involved gathering historical data on the daily closing prices of the sampled companies (Pi,t) and the Indonesia Composite Index (PIt) over the observation period. Next, we used the following formula to determine the market return (RMt) and stock return (Ri,t):

$$\mathbf{R_{i,t} = In\frac{P_{i,t}}{P_{i,t-1}}} \quad \text{.....(1)}$$

$$\mathbf{RM_t = In(\frac{PI_t}{PI_{t-1}})} \quad \text{.....(2)}$$

Using data from the estimation period, separate regressions were conducted for each firm to determine alpha (intercept) and beta (independent variable coefficient) values after collecting stock returns and market returns. The predicted return for the window period was computed using the alpha and beta values. Market model regression was used to calculate expected returns. The market model was chosen because this model can take into account the historical relationship between individual stock returns and market returns, thus capturing the effect of events on stock price movements (Mackinlay, 1997). By including alpha and beta parameters, the market model can identify abnormal returns arising from an event more precisely (Brown & Warner, 1985). The regression process was carried out using the following equation:

$$\mathbf{R_{i,t} = \alpha + \beta_i RM_t + \varepsilon_{it}} \quad \text{.....(3)}$$

After determining the alpha and beta values, the following formula was used to get the expected return of each stock E(Ri,t) for the window period:

$$\mathbf{E(R_{i,t}) = \alpha + \beta_i RM_t} \quad \text{.....(4)}$$

The difference between the actual return and the expected return for each day of the event window was then used to compute the daily abnormal return (ARi,t), which is expressed as follows:

$$\mathbf{AR_{i,t} = R_{i,t} - E(R_{i,t})} \quad \text{.....(5)}$$

The CAR was then determined using the following formula after receiving the abnormal return:

$$\mathbf{CAR = \sum_{t=1}^{N} ARi,t} \quad \text{.....(6)}$$

After calculating CAR, the next step was to conduct a regression test to see the effect of the complexity score generated by ChatGPT on CAR. Control variables in the form of number of pages, industry, company age, company size (size), and profitability in the form of Return on Equity (ROE) were added to the regression model to avoid biased results that can affect the relationship between complexity and company abnormal return (de Souza et al., 2019). Table 2 provides a thorough explanation of the variables, definitions, and data sources that were used in the research. The following formula is used to determine how complexity affects abnormal returns:

$$Y = a + b1X1 + e \qquad (7)$$

$$Y = a + b1X1 + b1C1 + b2C2 + b3C3 + b4C4 + b5C5 + e \qquad (8)$$

Table 2. Operational Definition of Variables

Variable	Definition	Source
Panel A. Dependent Variable (Y)		
CAR	Cumulative abnormal return around the annual report publication date. It is the total of abnormal returns from t−3 to t+3.	Own calculation
Panel B. Independent Variable		
Complexity (X1)	Level of textual complexity in the annual report. Score generated using ChatGPT on a scale from 1 to 10.	ChatGPT
Number of Pages (C1)	The number of MD&A pages in the annual report.	Annual report
Industry (C2)	A variable assigning numbers 1-11 to differentiate industry type.	idx.co.id
Company Age (C3)	The difference between the year of observation and the year the company was established is represented by the natural logarithm.	Eikon Refinitiv Database
Size (C4)	The natural logarithm of total assets, which serves as a measure of the company's size.	Eikon Refinitiv Database
ROE (C5)	The ratio of net income to shareholders' equity is known as return on equity.	Eikon Refinitiv Database

Before conducting regression testing, classical assumption testing was performed. The results of classical assumption testing showed heteroscedastic and non-normal distributed data with a Breusch-Pagan p-value < 0.05 and Shapiro-Wilk with p-value < 0.05. VIF testing, which the researchers also performed, revealed no multicollinearity between the independent and dependent variables. The Generalized Least Squares (GLS) method was employed in this study to test the hypothesis, as the data violated the classical assumptions of heteroscedasticity and normality. The GLS test was chosen because it is a regression model that is more effective than the OLS test, does not require normality assumptions, and can overcome autocorrelation and heteroscedasticity (Froot, 1998). The research hypothesis cannot be rejected if the p-value of the GLS regression test is <0.05.

4. Results and Discussion

Table 3 shows that the value of Abnormal Return (AR) tends to be negative in the three days prior to the publication of the annual report. The AR value begins to show a change in direction to positive on the day of the annual report publication. This positive trend continues until the day after the annual report publication, despite a decline on the first day after publication (AR on t+1). Before the report is released, the market will make estimates and speculations about the upcoming information (Syed & Bajwa, 2018). The market reacts to unexpected announcements about information disclosed by the company if the information differs from what the market expects. Before the report is published, the market shows a negative trend. The market is cautious ahead of the announcement due to uncertainty or concerns about the contents of the annual report (Syed & Bajwa, 2018).

Investors either sell in anticipation of potential negative information or refrain from buying shares because they have not yet obtained clarity about the company's information. This negative AR can also be caused by negative sentiment or negative information regarding the contents of the annual report based on the company's previous conditions, market rumors, or the results of the quarterly financial reports that have been released. There was no information leaking in the market before the annual report was released, as evidenced by a change in sentiment from negative to positive.

Table 3. AR & CAR Test Results

Var	Mean	Max	Min	Std. Dev	z-score	p-value
AR t-3	-0.0016	0.1043	-0.1851	0.0254	-1.4560	0.1453
AR t-2	-0.0005	0.3438	-0.4852	0.0392	-0.1980	0.8434
AR t-1	-0.0002	0.2275	-0.1942	0.0334	-0.8510	0.3949
CAR Before	-0.0024	0.3480	-0.5249	0.0538	-1.1420	0.2534
AR t_0	0.0017	0.3089	-0.2842	0.0371	2.3670	0.0179***
AR t+1	-0.0008	0.2912	-0.1932	0.0362	-1.0240	0.3060
AR t+2	0.0012	0.2875	-0.1497	0.0317	-0.7590	0.4476
AR t+3	0.0048	0.2943	-0.1409	0.0354	3.3030	0.0010***
CAR After	0.0052	0.6376	-0.3253	0.0585	1.3100	0.1902
CAR 7 days	0.0045	0.6749	-0.4691	0.0923	7.7580	0.0000***

Notes: *** significant at p-value <0.05 in Wilcoxon Signed Rank one-sample test.

AR has a positive average on the day of the annual report publication (see Table 3), indicating a reaction (p-value <0.05). The positive average on the day of publication shows that the actual stock performance is higher than market expectations. Positive AR occurs because before the annual report is published, the market tends to have overly low expectations. When the report is published, information that confirms or even exceeds investor expectations increases market confidence in the company's prospects, causing stock prices to rise and generating actual returns that are higher than expected returns. This indicates that the publication of the annual report successfully generated positive sentiment, resulting in AR. Positive sentiment occurs because when the annual report is published, the market obtains complete and verified information. This information helps reduce previous uncertainty and provides a more rational basis for investors to make decisions. Annual reports contain not only financial performance figures, but also narratives of management strategies in sections such as M&A (Li, 2008). If this section successfully builds market optimism by highlighting achievements, operational efficiency, future prospects, or growth strategies, investors can be more confident about the company's future direction, which ultimately drives positive sentiment in the market. If the annual report contains information that was previously unknown to the public, whether in the form of financial achievements, policy changes, or the company's future plans, this information will result in abnormal returns.

Table 3 also shows market reactions three days after the publication of the annual report (AR t+3) (p-value <0.05), indicating that the market still reacted after publication. This confirms that the annual report does indeed contain information that investors consider important. The information contained in the annual report is used by investors as a basis for making decisions and managing their investments (Chircop et al., 2024). The positive reaction on the third day indicates that investors need time to interpret the information into stock prices. This delay occurs because investors have difficulty understanding the contents of the annual report, which ultimately hinders their ability to process information (Boubaker et al., 2019). Complex annual reports can create ambiguity for investors and slow down the assimilation of information into stock prices (Li, 2008).

Investors need more time to update their estimates after the annual report is disclosed, especially when faced with annual reports with low readability (Xu et al., 2019).

Consistent with AR, Table 3 shows that the CAR value three days before publication (CAR Before) was negative on average and turned positive on the day the report was published (AR t0). This is reinforced by the Wilcoxon Signed Rank results at t0 ($p<0.05$), which indicate that there was a market reaction to the annual report on the day of publication. Positive CAR values continued to increase until three days after publication (CAR After). This shows that, cumulatively, the market experienced a change in sentiment from pessimistic to optimistic following the release of the annual report. This can also be demonstrated by the positive average CAR value in the event window. The change in sentiment from pessimistic to optimistic occurred because before the report was released, the market was in a state of uncertainty that triggered caution. However, after the report was published and showed clear performance that was often better than market expectations, the market responded positively. The clarity of information and optimistic narratives from managers are among the factors that change market perceptions of companies (Yekini et al., 2016).

The results of the Wilcoxon Signed Rank CAR 7 days (p-value <0.05) also indicate that the publication of annual reports successfully provided positive overall sentiment towards stocks. In addition, additional evidence can also be seen from the number of companies with positive CAR values (n=332) compared to companies with negative CAR values (n=255) at the time of report publication. This finding further reinforces that the publication of annual reports contains information deemed valuable by investors, thereby eliciting a positive market reaction. Based on AR and CAR tests, this study found that annual reports affect market reactions. Market reactions to the publication of annual reports are seen on the day of publication and several days thereafter. This indicates that market participants need time to read, understand, and process the information contained in the report thoroughly before making investment decisions. The existence of abnormal returns that occur at the time of the annual report publication and three days after it indicates that the market is not fully efficient, especially in the semi-strong form, because public information is not immediately reflected in stock prices. One possible cause of this delay is the high editorial complexity in annual reports. This complexity can hinder the process of understanding information, increase cognitive load, and ultimately delay the market's response to new information (Tan et al., 2015). The low readability of annual reports can cause a delay in market reaction, which ultimately results in the emergence of AR after publication.

Table 4 shows variations in the characteristics of annual report disclosures and financial performance indicators. The financial sector has the highest complexity score, indicating that annual reports in this sector are structured with more technical terms and tend to contain more complex narratives. This complexity may stem from the large number of reporting requirements and types of financial products that require detailed explanations (Li, 2008). Conversely, the healthcare sector has the lowest complexity score, indicating that the reports published tend to be easier to read. This difference confirms that the complexity of reports is not only influenced by technical content, but also by the writing style and information presentation structure used by each sector.

Table 4. Complexity by Sector

Sector	N	Complex	No of Pages	Age	Size	ROE	CAR
Financial	82	7.974	58.024	38.634	23.208	0.029	-0.007***
Consumer Non-Cyclicals	94	7.735	23.234	33.989	21.510	0.068	0.015***
Industrials	40	7.638	27.175	35.625	20.732	0.075	0.017***

Table 4. Complexity by Sector (Continued)

Sector	N	Complex	No of Pages	Age	Size	ROE	CAR
Technology	30	7.621	25.567	16.000	20.291	0.074	0.015***
Consumer Cyclicals	88	7.307	23.602	31.511	20.882	0.044	-0.002***
Basic Materials	66	7.221	26.576	35.121	21.944	0.048	-0.001
Infrastructures	38	7.191	44.395	30.237	22.169	0.075	-0.012***
Energy	51	7.174	28.412	27.216	22.722	0.145	-0.003
Properties & Real Estate	50	7.170	27.380	29.700	21.717	0.091	0.029***
Transport & Logistics	22	7.102	23.409	27.864	20.415	0.114	0.006
Healthcare	26	6.743	31.385	34.423	21.641	0.065	-0.006***

Notes: *** indicates significant value of the Wilcoxon Signed Rank test at p-value <0.05.

Consistent with the complexity scores, it appears that sectors with the highest complexity have the highest average number of pages. This reinforces the assumption that document length influences the difficulty of reading annual reports (Bloomfield, 2008). Conversely, the transport & logistics sector, which has relatively low complexity, also has a low number of pages. This indicates consistency between document length and readability. Company age and size also provide additional context to these findings. In the financial sector, the average age and size of companies again have the highest values. This identifies that larger and older companies tend to prepare reports with a more complex style, either due to regulatory requirements or reputational pressures (Lo et al., 2017).

However, the high complexity of reports does not always correlate with company performance. The financial sector, despite having the most complex reports, actually recorded the lowest ROE. Conversely, the energy as well as transport and logistics sectors, which have moderate to low levels of complexity, actually recorded the highest ROE. This identifies that complexity is not an indicator of financial excellence but can instead be used strategically to mask less favorable performance (Loughran & McDonald, 2014). Conversely, relatively simpler reports in the energy sector may indicate efficient communication that positively impacts market confidence. This aligns with previous research stating that companies with poor performance tend to increase report complexity to divert attention from unfavorable information (Bloomfield, 2008; Li, 2008).

From a market perspective, as indicated by CAR values, the publication of annual reports triggered market reactions in most sectors. Sectors experiencing CAR included properties & real estate, industrials, technology, consumer non-cyclicals, financials, consumer cyclicals, infrastructures, and healthcare. This response reflects that the annual reports released in these sectors contain information for investors that influences stock price movements. Meanwhile, three other sectors, namely basic materials, energy, and transport & logistics, did not show any CAR, indicating that the annual reports in these sectors did not bring enough new information or did not trigger market reactions. This result implies that the market does not see all annual reports equally and that investor responses to corporate information can differ based on market expectations and industry context. The presence of CAR in most sectors indicates that investors use the information contained in annual reports in their decision-making process.

As expected, Table 5 confirms that CAR is positively correlated with complexity. However, this result contradicts the initial assumption that there is a negative relationship between complexity and CAR. Meanwhile, the variables number of pages, company age, size, and ROE show a negative correlation with CAR. Overall, no high correlation was found between the variables in the model, confirming the results of the VIF test, which showed no multicollinearity.

Table 5. GLS Regression Results CAR

Variable	Model 1			Model 2		
	Coeff	Z-stat	p-value	Coeff	Z-stat	p-value
X1 (Complexity)	0.0104	13.9200	0.0000***	0.0142	18.9300	0.0000***
C1 (No of Pages)				-0.0069	-12.3700	0.0000***
C2 (Industry)				0.0013	11.5500	0.0000***
C3 (Age)				-0.0002	-10.9000	0.0000***
C4 (Size)				-0.0014	9.03000	0.0000***
C5 (ROE)				-0.0020	-22.0900	0.0000***
Wald chi		**193.67**			**1479.14**	
Prob chi		**0.0000*** **			**0.0000*** **	

Note: coefficient significant at ***p-value <0.05.

In presenting reports, language can influence investors' perceptions and understanding of the information provided (Morris et al., 2007). Narratives in corporate disclosures can convey information about a company's performance and expected value beyond quantitative disclosures (Bilinski, 2024). The use of technical and professional terms in annual reports can enhance investors' perceptions of a company's credibility and professionalism. The use of more complex words is often associated with companies that have high competitiveness and more mature business strategies (Zich, 2014). Previous studies generally interpret complex language in corporate disclosures as an indication of management obfuscation (Lo et al., 2017). However, the delivery of complicated information, like instructive technical disclosures, can also be reflected in complex language. Previous research has found that the informative component is negatively related to information asymmetry, meaning that the higher the informative and transparent components of a report, the lower the information asymmetry (Bushee et al., 2018). The informative component refers to the part of a report or company communication that provides clarity, transparency, and relevance of information to investors.

The findings of this study also indicate that managers were successful in building a positive impression among stakeholders. In this context, managers utilized strategic narratives and complex report structures to shape positive perceptions of the company. Managers have greater discretion in determining what, where, and how much information to present in annual reports, which ultimately poses challenges for analysis (El-Haj et al., 2020). By highlighting certain achievements and obscuring less favorable information through technical and difficult-to-interpret language, managers successfully direct investors' focus to desired aspects (Brown et al., 2024). This strategy does not necessarily eliminate negative information but rather packages it indirectly, leading investors to perceive the report as a sign of managerial professionalism and competence. As a result, the market responds optimistically to companies that can manage perceptions through narrative complexity, as reflected in positive stock returns.

On the other hand, complex reports may reflect factors that are largely beyond the control of the company, such as increased disclosure regulations or complex operational characteristics (Dyer et al., 2017). Regulations regarding annual report disclosure in Indonesia have evolved over time. Initially, these provisions were regulated in the Decree of the Chairman of Bapepam No. KEP-38/PM/1996 through Regulation No. X.K.6, which required issuers and public companies to submit annual reports as a form of basic information disclosure to investors. Over time, and with increasing demands for transparency and accountability, the Financial Services Authority (OJK) replaced these regulations with POJK No. 29/POJK.04/2016, which came into effect for the 2016 fiscal year. This regulation expands the scope of annual report content to include aspects of corporate governance, social and environmental responsibility, business risks, and a more structured management analysis and discussion. These changes reflect a shift from a purely administrative obligation toward a strategic approach in corporate communication with stakeholders.

Regulatory changes in Indonesia have brought about changes in the preparation of annual reports, including in terms of narrative and information disclosure. Previous studies have shown that regulatory changes tend to increase the complexity of accounting narratives due to the need to present more detailed, technical information that substantially reflects economic conditions (Efretuei et al., 2022). Indeed, regulatory changes have increased the complexity of accounting narratives, but this does not necessarily mean that information is obscured. In this context, complexity is seen as a consequence of higher reporting standards and substance-based principles, rather than an attempt by management to hide poor performance. In line with the results of this study, which show that the complexity of annual reports has a positive effect on CAR, this contradicts the research hypothesis (H1), which states that there is a negative effect. This indicates that the market views complexity as credibility or professionalism in reporting, rather than a form of obscuring information. Complexity in reports can actually be a reflection of compliance with reporting standards that are more accurate and informative about the company's financial position.

The impact of control variables including page count, industry, firm age, size, and ROE is also investigated in this study. Number of pages, company age, size, and ROE have a negative effect, indicating that the higher the value of these variables, the lower the CAR. These findings support the argument that information that is too long or complex tends to cause information overload and reduce the effectiveness of communication to investors (Li, 2008). Larger and older companies are often perceived as stable entities but are less likely to provide surprises or new information that is appealing to investors (Gu & Kurov, 2020). Conversely, industry variables show a positive influence, indicating that the industry sector affects investor perceptions and market reactions, as stated by previous researchers that industry characteristics play an important role in the interpretation of financial statements (Liu, 2020). The findings of the Wilcoxon Signed Rank test every sector, which indicate that eight of the eleven sectors exhibit market reactions to annual reports, support this. These findings provide evidence that market reactions to annual reports do indeed vary across industries, consistent with the information characteristics, investor expectations, and operational contexts of each sector. These findings underscore the importance of considering firm-specific factors when analyzing the influence of annual report complexity on market reactions.

5. Conclusion

This study utilizes artificial intelligence, specifically ChatGPT, to assist investors in analyzing the textual complexity of annual reports. The results indicate that the complexity score generated by ChatGPT has a positive effect on cumulative abnormal return. The findings remain consistent after incorporating several control variables in the regression analysis, including number of pages, industry, firm age, firm size, and return on equity (ROE). These results suggest that annual report complexity measured with the assistance of AI is relevant in influencing market reactions.

This study contributes to the emerging literature on AI-assisted textual analysis by examining annual report complexity in a non-English context. While prior research on financial disclosure readability has largely focused on English-language reports, relatively few studies measure annual report complexity in non-English settings using artificial intelligence tools. By analyzing Indonesian-language MD&A disclosures, this study demonstrates that AI-based textual analysis can be applied to evaluate narrative disclosures in emerging markets where corporate reporting often involves multilingual communication.

From a theoretical perspective, these findings are consistent with the principles of the Efficient Market Hypothesis, which suggests that financial markets respond to publicly available information. Narrative disclosures in annual reports, such as the Management Discussion and Analysis (MD&A) section, provide important qualitative information that investors use to evaluate firm performance and prospects. The ability of AI tools to capture narrative complexity therefore supports the idea that textual characteristics of corporate disclosures contribute to the information environment that shapes market reactions. In addition, the findings align with emerging perspectives in AI readability theory, which highlight the potential of artificial intelligence to enhance the measurement of readability and informational quality in corporate reporting.

From a practical perspective, this study provides insights for companies and regulators regarding the role of narrative disclosure in annual reports. Strategically structured and informative complexity in corporate reports may serve as an effective communication tool that shapes investor perceptions and potentially contributes to favorable market reactions. These findings also suggest potential policy implications for regulatory institutions such as Otoritas Jasa Keuangan and Indonesia Stock Exchange. Encouraging clearer and more standardized digital reporting practices may help ensure that corporate disclosures remain informative while still accessible to investors.

However, this study also identifies an important limitation in the use of generative AI models. During the analysis process, the outputs produced by ChatGPT were sometimes inconsistent even when the same prompts were used. This occurs because generative language models are probabilistic systems that may generate slightly different responses across interactions. Such variability presents a challenge when ChatGPT is used for measurement purposes that require repeatable and reliable results. Therefore, the development of standardized procedures and transparent prompt design is important to improve the reliability of AI-assisted textual analysis in academic research.

Future research could expand this study in several directions. First, subsequent research could repeat the analysis using multi-year datasets to examine whether the relationship between annual report complexity and market reaction remains stable over time. Second, cross-language validation between Indonesian and English versions of annual reports could provide additional insight into whether language differences affect the measurement of text complexity. Third, comparative studies using other large language models such as Gemini and Claude could help evaluate the reliability and robustness of AI-based text analysis across various generative AI systems.

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