GPT-4 Powered Virtual Analyst for Fundamental Stock Investment by Leveraging Qualitative Data

Teck Wan Teo
Department of Computer Science
Faculty of Information Communication & Techonology
Universiti Tunku Abdul Rahman
Kampar, Malaysia
teoteck0827@gmail.com

Soung-Yue Liew
Department of Computer Science
Faculty of Information Communication & Techonology
Universiti Tunku Abdul Rahman
Kampar, Malaysia
syliew@utar.edu.my

Chee Henn Chng
Department of Computer Science
Faculty of Information Communication & Techonology
Universiti Tunku Abdul Rahman
Kampar, Malaysia
cheehenn@gmail.com

Jing Ying Ng
Department of Computer Science
Faculty of Information Communication & Techonology
Universiti Tunku Abdul Rahman
Kampar, Malaysia
jypurz@gmail.com

Zong Zheng Khoo
Department of Computer Science
Faculty of Information Communication & Techonology
Universiti Tunku Abdul Rahman
Kampar, Malaysia
imzhengg@gmail.com

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***Abstract*— This paper introduces an advanced AI-assisted tool, powered by GPT-4, for fundamental stock investment, offering human-like investment advice accompanied by supporting information to validate recommendations for users. While traditional stock market prediction tools rely heavily on quantitative data such as stock prices, volume, earnings, and dividends, the use of qualitative data for stock market analysis is an emerging trend. Recent advancements in AI, particularly with Generative AI like ChatGPT, have significantly influenced user interactions and decision-making processes. Recognizing the potential of AI across various industries, we have customized GPT-4 to perform fundamental analysis based on news, financial and annual reports of companies, government policies, and more. Our tool analyzes the above qualitative data and provide numerical scores along with logical and fact-based justifications for the short, medium, and long-term investment prospects of companies. The system delivers reliable recommendations for up to ten months without continuous monitoring, making it valuable to a wide range of users, from value investors to everyday traders. The benefits of using our tool are substantial, including significant time and cost savings.**

Keywords—Stock Market Investment, Qualitative Data, Fundamental Analysis, Generative AI, Virtual Analyst

I. INTRODUCTION

Investing in the stock market offers an opportunity to supplement income. However, haphazard investments without thorough research can lead to financial losses. To enhance their chances of selecting stocks that will appreciate in value, individuals typically adopt one of two approaches: self-learning investment strategies or seeking the expertise of a fund manager. Self-learning requires investing a significant amount of time in reading reports, studying the prospects of listed companies, and attending investment training courses if necessary. On the other hand, hiring a fund manager to oversee investments usually involves substantial fees and is suitable only for the investors with large capital. Hence, these two approaches have their own limitations.

A more balanced approach that offers an efficient and economical way to enhance investment strategies is the conceptualization of a virtual analyst, which is the core of our proposed system. Rather than fully committing to studying stocks independently or relying solely on a fund manager, we propose exploring simpler methods, with the assistance of AI, for beginners to select suitable stocks. This approach leverages the advantages of both self-learning and expert guidance while mitigating their limitations.

The goal of this study is to develop a tool that enhances stock investment strategies from a fundamental perspective. This is achieved by leveraging Generative AI, such as ChatGPT, to analyze qualitative information, including company strategies, market insights, and government policies, to ensure that the investment recommendations made by the tool are fact-based and well-founded. The ultimate objective is to assist both novice and experienced investors in fundamental stock investment at a low cost. By using the historical data of selected stocks in Bursa Malaysia (the Malaysian Stock Market), our experiments show that the recommendations made by our system are valid for up to ten months, which is sufficient for value investing.

The remainder of the paper is organized as follows. In Section II, the related works are presented. We discuss the proposed idea and methodology in Section III. In Section IV, we compare the recommendations made by our system, based on the historical information (past news, reports, policies, etc), with the price movement of selected stocks, and show that the recommendations are valid for up to ten months. Finally, conclusions and future works will be discussed in Session V.

II. RELATED WORK

A. Investment Therories

To analyze stock performance, researchers have developed various theories. For example, the Efficient Market Hypothesis (EMH) assumes that in an efficient market, all the market information related to a stock will be fully reflected in the stock's price [1]. However, perfect market efficiency is an ideal assumption and does not always hold true in real-world scenario, leading some experts to disagree with EMH.

On the other hand, the Adaptive Market Hypothesis (AMH) is a more realistic theory that suggests market efficiency changes due to investor behaviours. It also indicates that the market does not strictly follow the economic principles but can be influenced by investor psychology. AMH proposes that market conditions evolve, allowing fundamental analysis to identify mispricing as markets adjust to new information. Furthermore, AMH supports the idea that patterns and trends resulting from investor behaviour can be identified and exploited through technical analysis, thereby aligning both fundamental and technical analysis with the adaptive nature of markets.

In short, many factors can affect the stock prices, typically categorized into economic and non-economic factors. However, it is widely accepted among experts that long-term stock price movements are intrinsically linked to the fundamentals of the stock.

B. *Quantitative Data Analysis*

Most deep learning algorithms for predicting stock prices rely on quantitative data. The survey papers [1], [2], and [3] discuss various models used for stock market prediction, highlighting their strengths and limitations. Artificial Neural Networks (ANNs) identify relationships between stock factors but require more relevant technical indicators to improve accuracy. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) enhance predictive accuracy but lack versatility and advanced feature extraction capabilities. Decision Support Systems (DSS) benefit from incorporating soft computing techniques to improve accuracy. Hidden Markov Models (HMMs) need to account for correlations between variables for better predictions. Support Vector Machines (SVMs) and Support Vector Regression (SVRs) should include macroeconomic factors to enhance their predictive power. Filtering methods require statistical tests to avoid data snooping bias, and fuzzy logic models should incorporate additional variables and techniques to handle non-stationary data. Optimization-based approaches benefit from advanced algorithms and data discretization methods.

Recently, an innovative method for predicting stock markets has emerged, leveraging generative AI with quantitative data. Chang Che and his team [4] utilized generative AI to replicate financial market data production mechanism. They applied a conditional generative adversarial network (cGAN) to generate synthetic financial data that accurately reflects the statistical properties of real market data. By using USD/JPY transaction data, which includes daily trading volume, opening price, highest price, lowest price, and closing price, the cGAN was able to create data that closely mimics actual market patterns. This technique enables generative AI to provide reliable predictions and insights, aiding investors and policymakers in making well-informed decisions in the financial market. However, the approach is devised for forex trading and disregards the fundamentals behind exchange rate movements.

Overall, integrating more sophisticated models and techniques can enhance the performance and versatility of these stock market prediction systems. However, for value investing, a thorough understanding of a stock's fundamentals is crucial. This requires qualitative information about companies, such as the nature of the business, the quality of management, and government policies, in addition to quantitative data like return on equity (ROE) and dividends. Thus, the aforementioned deep learning methods are inadequate for conducting qualitative analysis of stock fundamentals.

C. *Qualitative Data Analysis*

In the earlier days, generative AI was predominantly used for sentiment analysis, a key aspect of qualitative data analysis, to interpret and quantify sentiments expressed in textual data sources such as news articles and financial forums.

In [5], Lopez-Lira and Tang developed a ChatGPT-based sentiment analysis and linear regression model to predict short-term stock prices using CRSP daily returns and news headlines. Their model demonstrated a strong correlation between ChatGPT sentiment scores and next-day stock returns, outperforming other sentiment analysis methods. They suggest potential improvements with a hybrid system. In [6], Steinert and Altmann used GPT-4 and BERT for sentiment analysis on Stocktwits messages to predict Apple and Tesla's daily stock movements in 2017, finding GPT-4 outperformed BERT with better capture of nuanced sentiments and financial terminology. However, GPT-4's high deployment cost is a concern for practical use. Additionally, all the predictions focus on short-term stock market movements rather than fundamental analysis. The inputs used for analysis are limited to sources such as news headlines and forum data. These data sources capture market sentiment, which is more relevant to short-term investment prospects as they reflect investor behaviors and responses to immediate market movements.

Additionally, Udit Gupta developed GPT-InvestAR, a tool that assists in analyzing annual reports using ChatGPT [7]. It converts the detailed textual content of these reports into a structured dataset containing key financial metrics and sentiments about the company's performance and prospects. By combining this dataset with historical stock price data, the researchers developed a machine learning model to predict stock performance. The results were promising, showing that the model could outperform the S&P 500 index in return predictions. However, relying solely on annual reports is insufficient for a comprehensive evaluation of a company's performance and future prospects.

Studies have demonstrated that a Large Language Model (LLM), such as ChatGPT, has the potential to analyze qualitative data in the stock market. Our idea is to leverage various qualitative data sources such as annual reports, quarterly reports, company news, and government policies to conduct fundamental analysis on companies. This approach aims to overcome the limitations of solely relying on quantitative analysis. By incorporating these diverse data sources, we can provide comprehensive recommendations and justifications for not only short-term but also medium and long-term investment prospects.

III. METHODOLODY

To realize the concept of a virtual analyst, we will train GPT-4 from OpenAI to analyze financial qualitative data and provide numerical ratings along with justifications to users. This approach is necessary because, while GPT-4 possesses broad general knowledge, it may lack deep expertise in the stock market investment and does not have real-time access to the relevant data.

As depicted in Fig. 1, the system's workflow is divided into two segments: admin and user. The admin segment, highlighted in light red, involves acquiring and preprocessing data, managing databases, and refining the model to enhance performance. In contrast, the user segment, highlighted in light blue, focuses on user interaction with the system via the GUI, allowing users to explore and gather information about various company stocks.

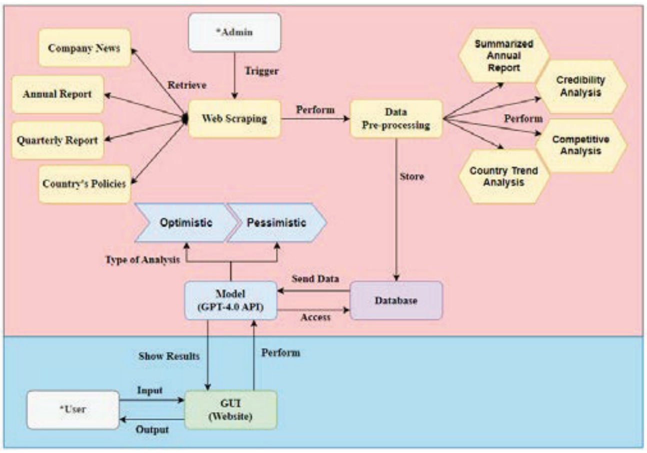

Fig. 1. System's Workflow.

A. Data Sources

The system gathers information from four primary sources: company news, annual reports, quarterly reports, and national policies. To streamline the collection process, we use web scraping tools to efficiently gather data from the Internet. While these four sources are essential for the analysis, the system is designed to be expandable, allowing the incorporation of additional data sources to enhance the accuracy of its recommendations.

B. Data Pre-processing

To handle the qualitative data, we utilize GPT-4 to summarize the data by configuring specific tasks for it to complete. Instead of completing all tasks on the "Model" depicted in Fig. 1, we have opted to distribute the tasks across multiple GPTs to preprocess the data before it serves as input for analysis. This approach not only reduces the number of input tokens required but also lowers the costs associated with calling the GPTs. We have designated four separate GPTs to handle distinct tasks, as follows:

i. Summarized Annual Report

In the company annual report, we concentrate on three principal sections: the board of directors, the chairman's statements, and the management discussion and analysis. For the board of directors, the designated GPT is tasked with retrieving their names and respective roles. In the chairman's statements, the GPT focuses on extracting insights about the company's performance, strategic direction, governance practices, challenges and opportunities, future prospects, sustainability, risk management, industry trends and competitive landscape. The management discussion and analysis covers similar areas as the chairman's statement but also includes detailed evaluations of their business segments and annual performance. This structured format will facilitate efficient storage in our database.

ii. Credibility Analysis

Credibility analysis is conducted to verify whether the management or chairman of a company has met their stated targets. For example, if the chairman commits to digitalizing operations but no digitalization efforts are evident in the following year, this will reflect poorly on their credibility. To perform this analysis effectively, it is essential to review multiple years of annual reports to check the consistency of their stated goals against actual achievements. In our system, the input consists of multiple years of annual reports. The GPT is tasked with extracting forward-looking statements, challenges faced, any subsequent follow-through, and the implementation of future directions. The output will provide an analysis of the implementation of future directions, interpretation of sentiments, and the challenges and solutions identified.

iii. Competitive Analysis

The purpose of conducting competitive analysis is to enhance the realism of our results. Focusing solely on the selected company might not provide sufficient insight into its industry positioning. By comparing strengths and weaknesses relative to its competitors, users gain a clearer understanding of the company's competitive landscape. However, in our system, competitors are manually identified, and typically only one or two are shortlisted for comparison. We utilize the latest quarterly reports to assess current industry performance, adapt credibility analysis to evaluate the integrity of management, and review recent news to compare their current activities. The GPT is tasked with comparing the selected company and its competitors by assessing their market position, performance, financial status, strategic initiatives, credibility, and risk. The output will be a performance ranking within the industry, ranging from 1 (highest) to 2 or 3 (lowest). Each ranking will be accompanied by a detailed justification, providing clear insights based on the comparative analysis.

iv. National Policy Analysis

To perform market analysis for a country, we focus on policies with the highest impact and attention from both the government and investors, rather than studying all policies from various departments. However, we encountered challenges due to the broad scope of these policies, which may lead GPT-4 to randomly select from a wide range of targeted industries for prediction. For instance, "Policy X" covers sectors like aerospace, food processing, and automotive. To enhance our analysis, we incorporate "Progress News" to provide current context. For example, "Company Y" announces the construction of its largest 3D chip packaging facility in a particular city, this information is relevant to the semiconductor sector included in "Policy X". Integrating policy analysis with recent developments allows the model to identify and predict market trends more accurately.

C. Model

The GPT API will be the core model in our system, utilized to analyze data and provide recommendations with supportive evidence to users. This choice is based on its proven results and capabilities, as demonstrated in other research. However, cost considerations are significant, as the GPT-4 Turbo API model costs $0.01 per 1000 tokens for input and $0.03 per 1000 tokens for output. This expense is relatively high compared to other models, necessitating careful pricing strategies for deployment.

Additionally, the model is designed to operate like a virtual skilled investment analyst, primarily processing qualitative data from various sources such as the latest annual reports, the most recent quarterly reports, credibility analyzes, competitor analysis, and trends in the country. It leverages its database, with the current knowledge cut-off for the GPT-4 Turbo Model being December 2023. The model is programmed to carefully consider factors such as leadership changes, market position, and management credibility while focusing on generating clear and actionable investment recommendations. The model's outputs are categorized into three-time frames: short-term (3-6 months), medium-term (6 months to 1 year), and long-term (1 year onwards). Each period concentrates on distinct aspects such as recent financials for the short term, market positioning and credibility analysis for the medium term, and strategic initiatives and business alignment with the trends for the long term. The system issues recommendation ratings on a scale from 0 to 10, accompanied by supporting evidence, and includes an assessment of the company's credibility.

Moreover, we demonstrate that ChatGPT can embody distinct perspectives, opening new avenues for research into how different experts might interpret the same information differently. By configuring ChatGPT with both optimistic and pessimistic versions, we allow it to analyze data from these differing viewpoints. For example, the headline "Company A Continues to Cut Prices Across Its Car Range" might be viewed by an optimistic analyst as a sign of Company A's manufacturing efficiency and market confidence. In contrast, a pessimistic analyst might interpret it as an indication of demand issues and potential profitability challenges.

The optimistic analyzer (GPT) will emphasize positive aspects of information, such as financial growth, potential for increased demand, and a generally positive long-term outlook. On the other hand, the pessimistic analyzer focuses on identifying management vulnerabilities, exploring potential risks to the company, and critically assessing whether the company is truly prepared to scale production to meet increasing market demands, despite alignment with current trends. These two approaches provide distinctly contrasting perspectives on the same data.

D. Model Configurations

When using the GPT API, an important parameter to consider is "temperature," which controls the randomness or creativity of the model's responses. This parameter is set as a numerical value typically ranging from 0 to 2. A low temperature, closer to 0, results in more deterministic, consistent, and predictable responses, making it ideal for tasks requiring high precision and minimal variability. Conversely, a high temperature, closer to 2, makes the model's responses more varied, random, and creative. This setting allows the model to produce a broader array of outputs and engage in more experimental language generation, which is beneficial for creative tasks or scenarios where exploring diverse response options is preferred.

In our system, we assign different temperature settings to different GPTs based on the tasks they perform. For instance, for all data preprocessing tasks, the temperature is set to 0. This ensures that the responses are strictly factual and reliable, avoiding any generation of inaccurate or fabricated content. For interactive sessions where users consult the analyzer (GPT), we set the temperature to 0.2. This allows for responses that are primarily based on factual justifications, while still permitting a slight degree of creative interpretation in the answers provided. By implementing these temperature settings, we ensure our system's reliability, delivering fact-based analysis rather than speculative content.

Additionally, we have structured the prompts for the analyzer (GPT) to follow step-by-step instructions set by either the admin or the user, allowing for customization based on specific user requirements. The prompt system includes two distinct roles: the "system role" and the "user role." The system role provides instructions and rules for the GPT, ensuring it adheres to the desired guidelines. The user role represents the person interacting with the GPT, similar to how users typically interact with ChatGPT. We propose a structured format to ensure our analysis is consistent, resulting in uniformly structured and reliable outputs. For the system role, we focus on analyzing different terms and require a numerical rating for each one. For the user role, we emphasize providing relevant data inputs and any additional information GPT needs to consider, while clearly defining the desired output format. The general format is illustrated in Fig. 2 (System role) and Fig. 3 (User role).

```
"role": "system",
"content": f"""As a skilled investment analyst, your primary responsibility is to
conduct a comprehensive analysis of companies using a diverse array of informational resources.

Instructions for Comprehensive Analysis:
1. Short-Term Investment Potential Analysis (3-6 months) for [{company}]:
  [Primary data can be customized to focus on short-term investment analysis.]

2. Medium-Term Investment Potential Analysis (6 months to 1 year) for [{company}]:
  [Primary data can be customized to focus on medium-term investment analysis.]

3. Long-Term Investment Potential Analysis (1 year onwards) for [{company}]:
  [Primary data can be customized to focus on long-term investment analysis.]

4. Qualitative Assessment and Investment Rating:
  - Provide a qualitative assessment and a numerical rating (0-10) for each investment
  term (short, medium, and long-term), based on a detailed examination of the documents
  and market analyses.

This guidance is structured to facilitate a thorough, balanced, and data-driven analysis,
ensuring an exhaustive understanding of each company's investment potential. Your analysis
should seamlessly integrate these assessments, highlighting the company's market alignment,
credibility, and competitive standing."""
```

Fig. 2. Prompt Structured Format of System Role.

```
"role": "user",
"content": f"""Objective: [Primary analysis for GPT.]

Data Provided for Analysis:
[Necessary Data.]

Enhanced Instructions for Analysis:
[Extra notes for GPT. / E.g. Telling GPT must be candid and not bias while doing analysis.]

Response Format:
[Customizable Output Format.]"""
```

Fig. 3. Prompt Structured Format of User Role.

IV. Result

Before evaluating the results, it is crucial to ensure that all justifications generated by GPT are fact-based rather than speculative, guaranteeing the system's reliability at 100%. To achieve this, we utilize a lower temperature setting, as mentioned earlier.

To evaluate the numerical ratings and their corresponding justifications, we verify their accuracy in predicting future outcomes. Our evaluation method involves selecting a past period and instructing GPT to forecast a future period. We then compare these predictions with actual stock price data to determine their accuracy. For example, we choose January 1, 2018, as the benchmark date and predict stock performance over the next five years, ending on December 31, 2022. We also select companies within the same sector to evaluate the competitive landscape among them.

A. Terms Evaluation

The evaluation process encompasses three distinct terms: short-term (3 to 6 months), medium-term (6 months to 1 year), and long-term (1 year and beyond). This analysis employs two types of GPT analyzers: the optimistic analyzer, and the pessimistic analyzer, which both emphasize different aspects, as discussed previously. Users can refer to the summary rating table generated by both analyzers, as each provides a different range of ratings. These ratings classify company's situation as negative, neutral, or positive.

TABLE I. REFERENCES OF RATING CATEGORIES

Type of Analyzers (GPTs)	Rating Categories		
	Negative	*Neutral*	*Positive*
Optimistic	0 - 5	6 - 7	8 - 10
Pessimistic	0 - 4	5 - 6	7 - 10

Our experiments indicate that the pessimistic analyzer tends to reflect reality more accurately, as its predictions align more closely with actual stock prices compared to the optimistic version. Hence, our team recommends using the pessimistic analyzer for more reliable justification, as it provides a more realistic assessment of potential risks and challenges faced by the companies.

Examples of the rating categories using the pessimistic analyzer are as follows (Note: Company names will be replaced with letters):

i. Positive & Neutral (*Company P*)

According to the short-term investment prospects, GPT assigned a rating of 7 to Company P, predicting a positive performance within 3 to 6 months. This is supported by the actual stock price data: starting at RM 5.20 on January 1, 2018, and rising to RM 5.97 by June 30, 2018, indicating an increase that aligns with GPT's analysis.

Aside from the positive category, there is the neutral category as shown in the medium-term outlook of company P. GPT assigned a rating of 6, reflecting a neutral stance on the company's performance over the second half of the year. GPT noted potential challenges the company might face and suggested monitoring the company's response to these situations. The stock price remained relatively stable around RM 5.80 throughout the second half of the year, with no significant increase or decrease until a notable drop in December, which was not accurately predicted. The references are shown in Fig. 4.

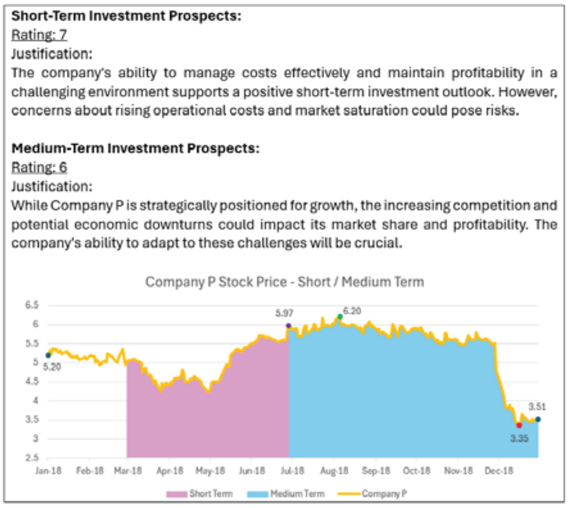

Fig. 4. References of Company P Investment Prospects & Stock Price

ii. Neutral (*Company Q*)

For the short-term outlook, GPT assigned a rating of 6 to Company Q, highlighting both its strengths and weaknesses. This resulted in a neutral market stance, reflected in the stock price remaining stable at RM 0.07 from the beginning to the end of the short term. In the medium-term outlook, GPT maintained its neutral attitude towards Company Q. According to GPT's justification, it believes that Company Q has growth potential but is not yet ready to fully capitalize on it. The stock price remained at RM 0.07 at the end of 2018, accurately reflecting GPT's prediction. The references are shown in Fig. 5.

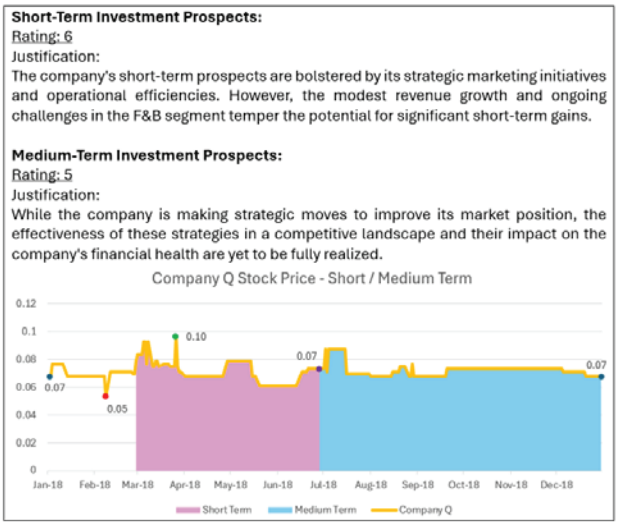

Fig. 5. References of Company Q Investment Prospects & Stock Price

iii. Negative (*Company R*)

GPT assigned a short-term rating of 3 to Company R due to a revenue drop and increased internal costs. This rating is validated by the decline in stock price from RM 1.47 to RM 1.17 over six months. For the medium-term outlook, GPT also gave a negative rating, primarily due to concerns about the effectiveness of the company's strategies and the competitive landscape. This negative outlook was further confirmed as the stock price dropped from RM 1.17 to RM 0.62 by the end of the year. The references are shown in Fig. 6.

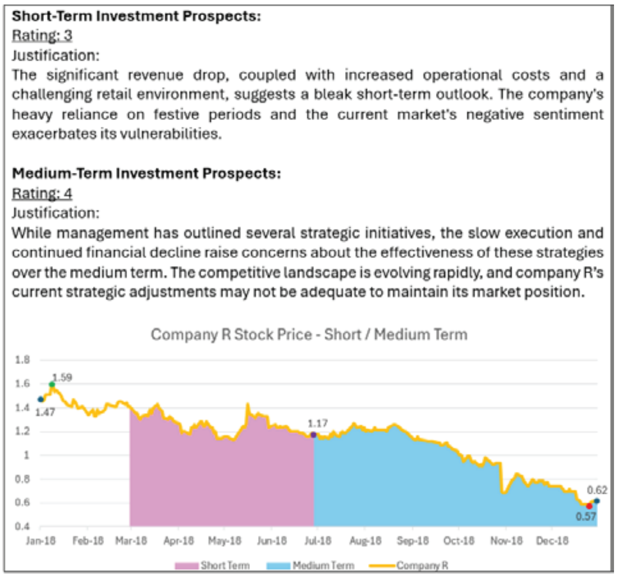

Fig. 6. References of Company R Investment Prospects & Stock Price

B. Competitive Landscape Evaluation

The competitive analysis examines the recent performance of companies relative to their industry competitors, similar to the short-term analysis. GPT ranked Company P the highest, followed by Company R, and then Company Q, based on their recent performance. This ranking is supported by the actual short-term stock price results. As shown in Fig. 7, Company P's stock price increased, Company R's stock price remained stable, and Company Q's stock price declined. These results align with GPT's rankings.

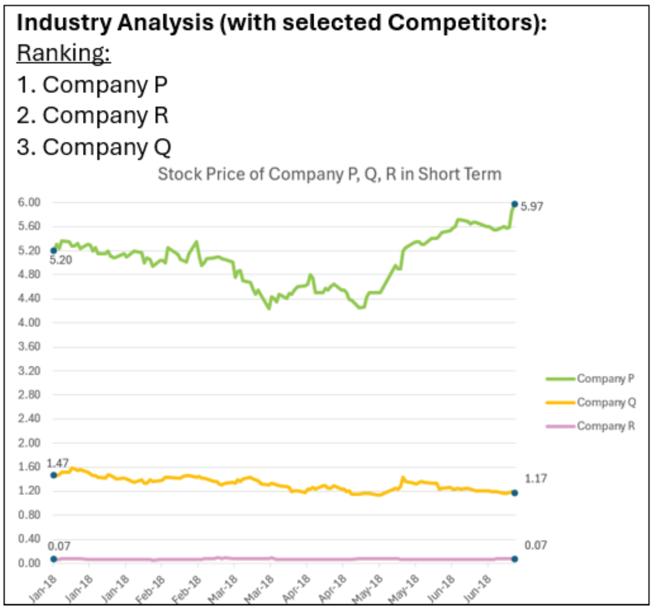

Fig. 7. References of Company P, Q, R's Stock Price in Short Term Period

C. Long Term Investment Evaluation

One evaluation example is Company R, as shown in Fig. 8. GPT provided a neutral rating for Company R, acknowledging its growth potential but maintaining a neutral stance due to its historically poor performance. However, the actual results showed that the company experienced growth, with its stock price increasing over the five years from 2018. This outcome contrasts with GPT's initial justification.

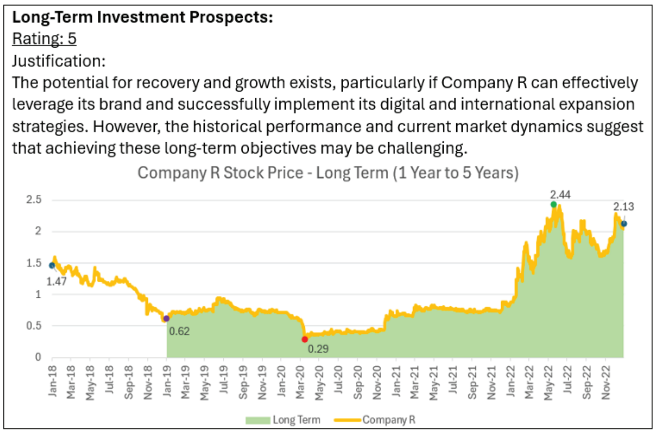

Fig. 8. References of Company R Investment Prospects & Stock Price in Long Term

Based on observations, mis-justification primarily occurs in most companies due to the challenge of using initial data to predict outcomes beyond one year. This difficulty arises from the multitude of unexpected variables or incidents that can occur over time. However, our system can provide more reliable recommendations for up to ten months without continuous monitoring, relying solely on initial data.

Continuous monitoring of stock investments is crucial due to the inherent market volatility, where stock prices can change rapidly in response to market conditions, economic events, and shifts in investor sentiment. This volatility makes it challenging to accurately predict and provide recommendations based solely on initial data.

V. Conclusion

In this paper, we present an innovative method for making informed stock investments that goes beyond the traditional options of self-learning or hiring fund managers. Our system leverages qualitative data to complement and address the limitations of quantitative-only approaches. By integrating company information with the capabilities of the GPT model, our system provides reliable investment justifications for up to ten months without requiring continuous updates. This approach offers significant time and cost savings, making it an efficient and effective tool for investors.

To improve our system, we plan to implement notifications to alert users of database updates, enabling continuous stock market monitoring. We will incorporate OCR (Optical Character Recognition) technology to automate data_extraction from PDFs, making the information more accessible. Additionally, we will integrate global market data for comprehensive analysis and expand our capabilities by analyzing a company's customer base and its revenue relationship, providing new analytical insights.

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