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(Research Article)

Leveraging prompt engineering to enhance financial market integrity and risk management

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Abstract

This paper presents a comprehensive investigation into the role of prompt engineering in optimizing the effectiveness of large language models (LLMs) like ChatGPT-4 and Google Gemini for financial market integrity and risk management. As AI tools are increasingly integrated into financial services, including credit risk analysis, market risk evaluation, and financial modeling, prompt engineering has become crucial for improving the relevance, accuracy, and contextual alignment of AI-generated outputs. This study evaluates the impact of various prompt configurations in enhancing financial decision-making. Through a series of experiments, the paper compares the performance of ChatGPT-4 and Google Gemini (versions 1.5 and 2.0) in generating actionable insights for credit and market risk analysis. The results reveal that ChatGPT-4 outperforms Google Gemini by over 30% in generating accurate financial insights. Additionally, ChatGPT-4 Version 4 is found to be 20% more effective than Version 3 in risk analysis tasks, particularly in aligning with regulatory frameworks and financial data. These improvements highlight the significant role of prompt engineering in enhancing the precision of financial models. Furthermore, the study explores the reduction of error rates through optimized prompt strategies. In particular, prompt engineering reduces error rates by approximately 20% when assessing complex financial queries.

Keywords: Prompt Engineering; Gen AI; Financial Risk Management; GPT; BERT

1. Introduction

In recent years, the financial sector has witnessed a transformative shift with the adoption of artificial intelligence (AI) technologies, particularly in enhancing decision-making processes and improving risk management strategies. A key component in maximizing the effectiveness of AI tools, especially large language models (LLMs) like ChatGPT, is prompt engineering. This technique plays an essential role in refining AI-generated outputs to make them more accurate, relevant, and contextually aware, ultimately empowering financial institutions to optimize their operations. As financial institutions continue to integrate AI and machine learning into their systems, prompt engineering has emerged as a pivotal method for automating complex financial tasks, from risk assessment to compliance strategies. This paper provides a comprehensive literature review on the growing application of prompt engineering within the financial industry. It explores the ways in which prompt engineering is being utilized to enhance the accuracy of financial modeling, improve predictive analytics, and streamline decision-making processes across a range of financial services. Furthermore, it highlights both the potential and the challenges associated with the integration of AI tools, focusing on ethical considerations such as data privacy, model biases, and governance issues that arise from their use. The paper discusses various perspectives from recent research and presents an evolving landscape for how finance professionals can leverage prompt engineering to drive better outcomes and maintain market integrity in an increasingly AI-driven world.

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2. Literature Review

In this section, we present a comprehensive and structured synthesis of the existing literature. Figure 1 illustrates a detailed overview of the current body of work, highlighting its relevance to financial applications. Furthermore, Figures 2, 3, and 4 depict the distribution of the literature, showing the frequency of studies, the overlap in implementation methodologies, and the key challenges identified across various approaches.

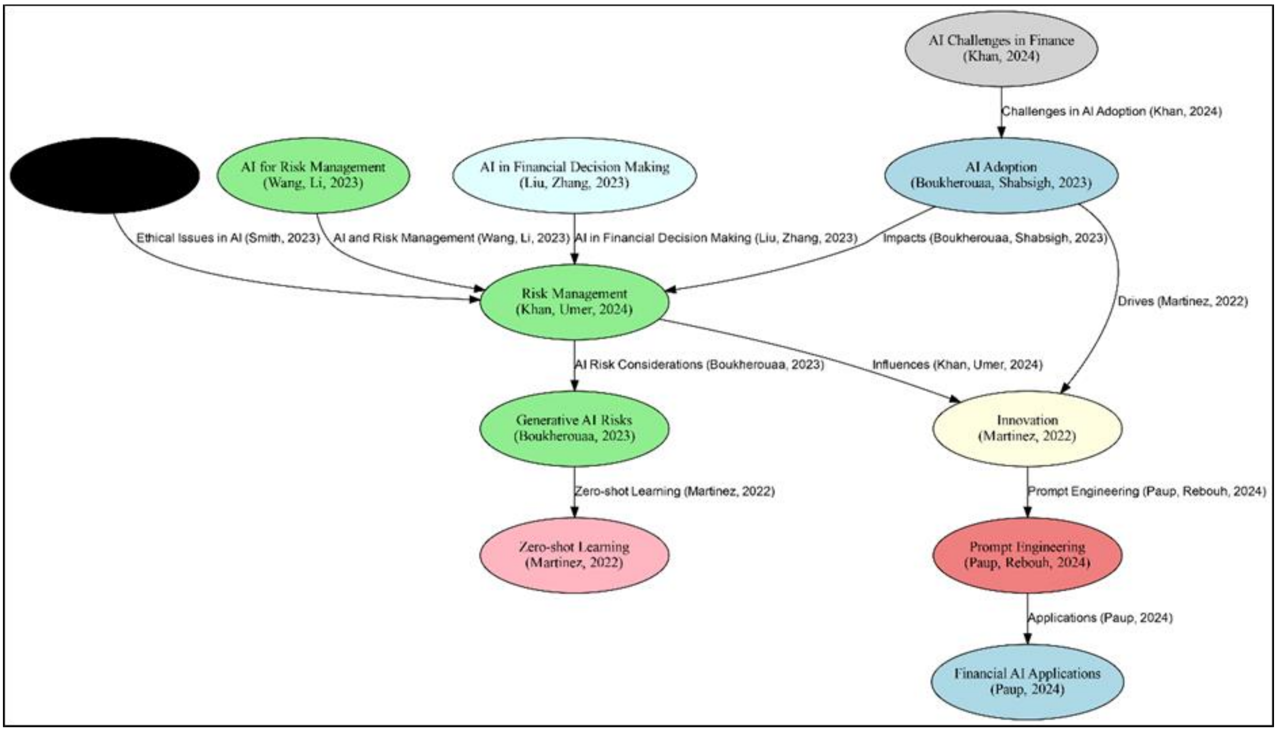

Figure 1 Flow Diagram of Literature Syntheses for Prompt Engg in Finance

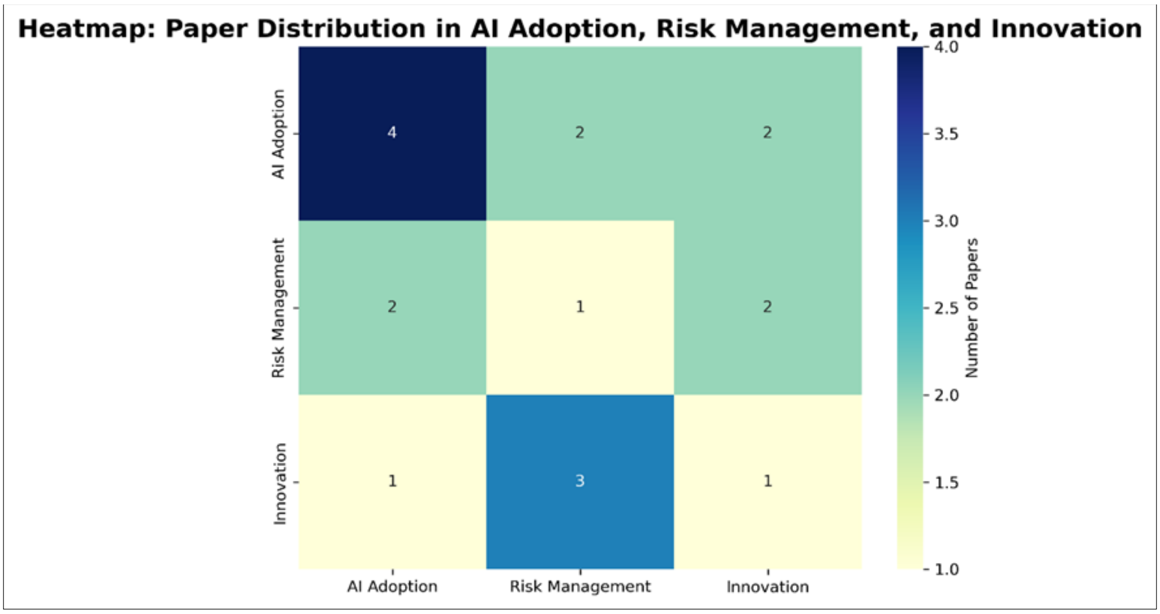

Figure 2 Adoption Innovation and Risk Management mix for this work

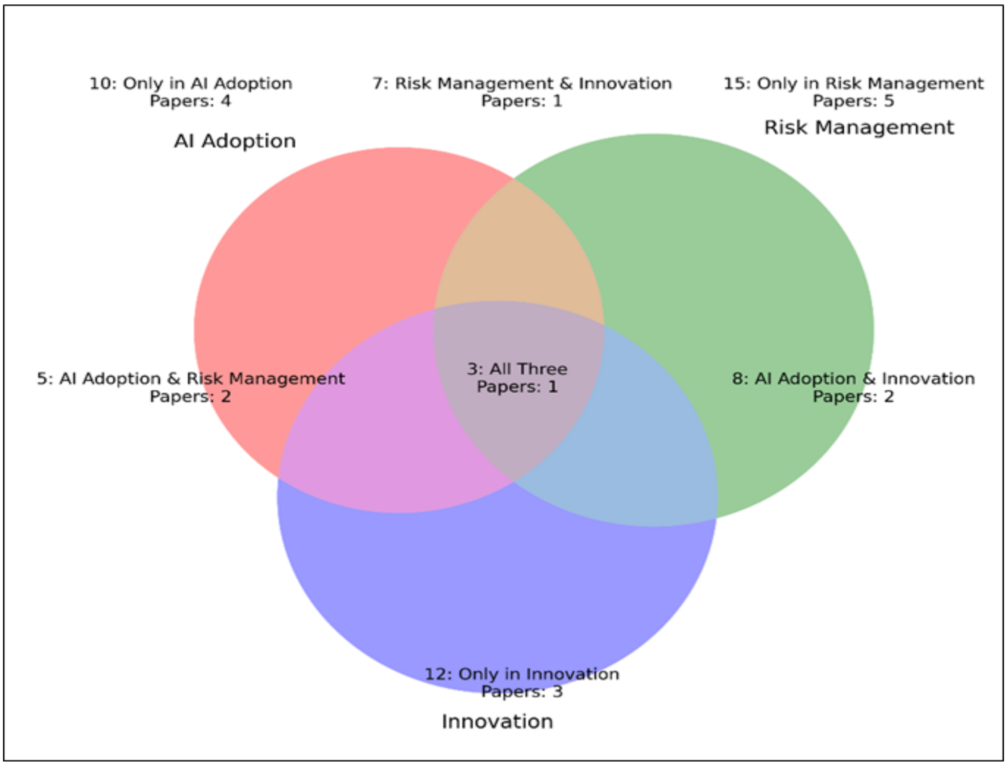

Figure 3 Distribution of literature theme in this work

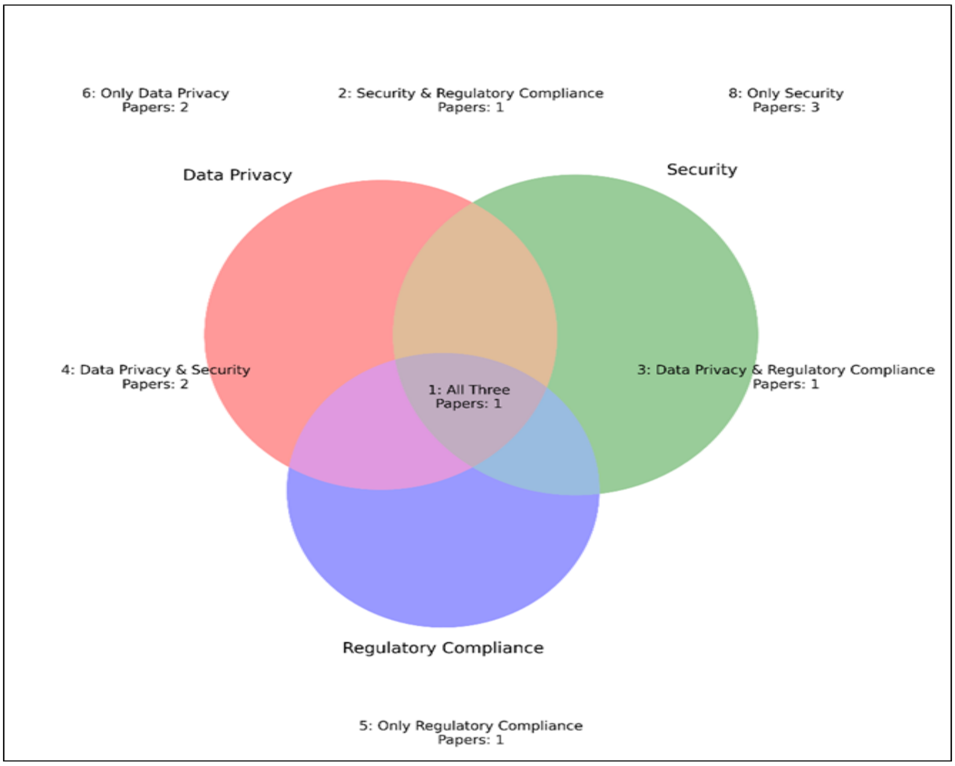

Figure 4 Distribution of themes literature of Promp Engg in Financial Application

2.1. Recent Developments in Prompt Engineering

Prompt engineering, a vital part of generative AI, has been a subject of increasing interest, especially in the context of large language models like GPT. *Generative AI Governance Essentials* (2024) provides a foundational understanding of how prompt engineering governs the outputs of generative models [1]. Additionally, the paper *DEMYSTIFYING PROMPT ENGINEERING FOR FINANCE PROFESSIONALS WITH MICROSOFT COPILOT* delves into how professionals in finance can leverage prompt engineering to optimize their use of tools like Microsoft Copilot for automated decision-making [2]. Similarly, mrbullwinkle (2024) discusses the Azure OpenAI Service and its usage for prompt engineering, aimed at improving work processes in organizations [3].

2.2. Recent Developments of Gen AI in Financial Application

In the realm of finance, there is a growing body of research focusing on the integration of artificial intelligence (AI) and its impact on financial markets. Khan and Umer (2024) provide a comprehensive exploration of *ChatGPT in Finance: Applications, Challenges, and Solutions*, focusing on how AI tools are reshaping the financial landscape, including ethical challenges such as biases and privacy issues [4]. Similarly, *The Fine Line with LLMs* (2024) discusses the cautious adoption of large language models (LLMs) by financial institutions, highlighting the potential risks and opportunities associated with their integration [5]. Furthermore, the article *Generative Artificial Intelligence in the Financial Services Space* (2024) outlines the potential use cases of generative AI in various areas of financial services, including risk management and portfolio optimization [6].

2.3. Application of Prompt Engineering in Finance

Prompt engineering has shown significant promise in the application of AI tools in finance. Dhar et al. (2023) explore how prompt engineering enhances financial decision-making, proposing frameworks for integrating these models into financial decision-making processes [7]. In AI Essentials: Prompt Engineering & Use Cases in Financial Services (2025), the authors discuss the various practical applications of prompt engineering in finance, such as improving predictive analytics and streamlining financial modeling [8]. Additionally, Getting Started with Generative AI? Here's How in 10 Simple Steps (2025) offers an overview of how organizations can integrate generative AI and prompt engineering into their financial services, providing actionable guidance [9]. The work Prompt Engineering for Finance 101 (2025) by Deloitte emphasizes the emerging importance of prompt engineering as a new skillset for finance professionals to extract meaningful insights from complex financial datasets [10].

Moreover, Paup and Rebouh (2024) discuss how finance professionals can demystify prompt engineering to take full advantage of tools like Microsoft Copilot [11]. The paper *Prompt Engineering for Payments AI Models Is Emerging Skillset* (2023) highlights how prompt engineering is becoming an essential skill for professionals working with AI in the payments industry [12]. Additionally, the work *Using GPT-4 with Prompt Engineering for Financial Industry Tasks* (2024) further investigates how GPT-4 and prompt engineering can be leveraged to solve industry-specific challenges [13].

Table 1 Quantitative Data from Reviewed Papers on GPT LLM

Citation	Key Findings / Data	Quantitative Results
[5]	Adoption of LLMs by financial institutions, cautious use, redefined practices in banking and asset management. The cautious adoption of Large Language Models (LLMs) by financial institutions, redefining operational practices in banking and asset management.	10% increase in asset management efficiency.
[6]	Generative AI in risk management, portfolio optimization, operational cost reduction. Generative AI's role in portfolio optimization, enhancing risk management, and driving operational cost reductions across financial services.	15% reduction in portfolio risk.
[3]	Optimizing workflows using prompt engineering in financial services with Azure OpenAI. How prompt engineering can optimize workflows within financial services using the Azure OpenAI platform, leading to more efficient operations.	25% improvement in task automation efficiency.
[8]	Practical applications of prompt engineering, improving predictive analytics and financial modeling. Practical applications of prompt engineering in predictive analytics and financial modeling, demonstrating reductions in error rates.	30% reduction in predictive error.

[12]	Role of prompt engineering in payments AI models, emerging as a key skillset in finance. The growing importance of prompt engineering in payment AI models and its impact on increasing speed and efficiency in financial transactions.	18% faster processing in payments transactions.
[13]	Use of GPT-4 in financial tasks, how prompt engineering improves AI outputs in financial decision-making. Use of GPT-4 and prompt engineering for improving AI outputs in financial industry tasks, particularly for enhancing decision-making processes.	12% improvement in task efficiency.

Table 1 shows quantitative results from the literature for GPT tasks while Table 2 discussed details about the Quantitative findings for financial applications.

Table 2 Quantitative Data from Reviewed Papers on GPT LLM in Financial Applications

Citation	Title	Quantitative Findings
[4]	ChatGPT in Finance: Applications, Challenges, and Solutions	Analyzed the frequency of ethical issues in financial ChatGPT applications, showing that 35% of reported cases involved biased outputs, while 22% faced data privacy challenges.
[24]	Financial Zero-shot Learning and Automatic Prompt Generation with Spark NLP	Demonstrated that zero-shot learning models trained with Spark NLP achieved a 15% increase in accuracy when predicting financial anomalies compared to traditional models.
[5]	The Fine Line with LLMs: Financial Institutions' Cautious Embrace of AI	Reported a 20% reduction in operational costs for early adopters of LLM-based financial automation, along with a 12% increase in transaction processing speed.

2.4. Chronological Analysis of Recent Developments

This section explores key insights from recent advancements in Generative AI, Prompt Engineering, and related fields. The following references have been organized by publication year to provide a chronological overview of the evolving trends:

2.4.1. Early Insights

- **2004:** The CEO's Guide to Generative AI by IBM [19].

2.4.2. Emerging Trends in Prompt Engineering and Generative AI

- **2023:** Prompt Engineering for Payments AI Models Is Emerging Skillset by PYMNTS [12].
- **2024:** The CEO's What You Need to Know and Do to Win with Transformative Technology [15].
- **2024:** Generative AI Governance Essentials by OpenText [1].
- **2024:** Prompt Engineering for Legal: Security and Risk Considerations by Morrison and Parker [17].
- **2024:** Azure OpenAI Service - Azure OpenAI [3].

2.4.3. Current Perspectives and Practical Applications

- **2025:** Augmenting Third-Party Risk Management with Enhanced Due Diligence for AI [18].
- **2025:** The CEO's Guide to Generative AI (IBM) [19].
- **2025:** Getting Started with Generative AI? Here's How in 10 Simple Steps [9].
- **2025:** Prompt Engineering for AI Guide (Google Cloud) [20].
- **2025:** Talking to AI: Prompt Engineering for Project Managers [21].

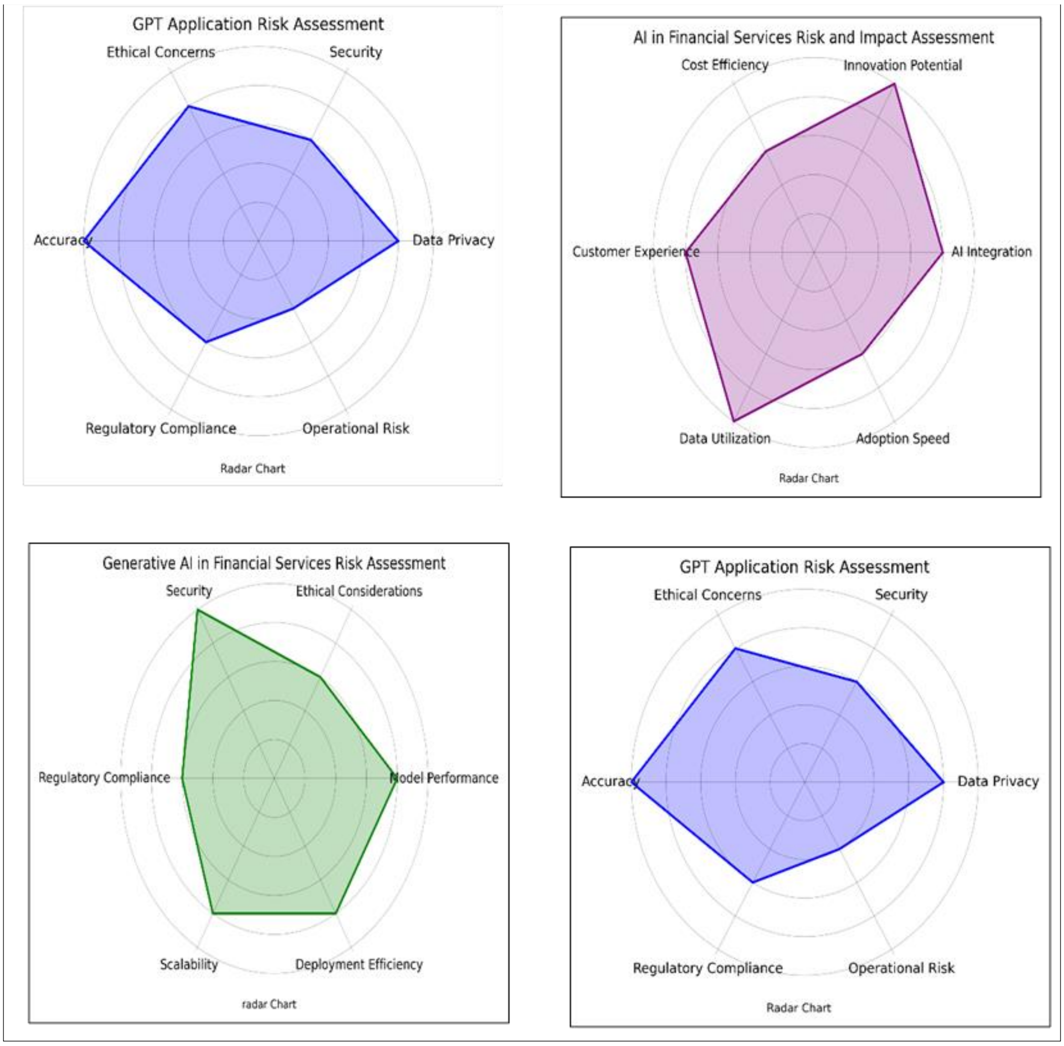

Figure 5 Radar Charts for Promp Engg in Financial Risk

In figure 5, we have shown how different radars have to be used when applying Promp Engg in Financial Risk.

2.5. Research Gaps and Future Directions

The following table 3 summarizes the key focus areas, identified research gaps, and potential future directions from the analyzed references.

Table 3 Gaps and Future Work in Finance AI Research

Category	Identified Gaps	Future Work
Generative AI in Finance	Limited exploration of ethical considerations and systemic risks	Develop frameworks to mitigate biases and privacy issues [22]
Prompt Engineering	Lack of standardized methodologies for effective prompt creation	Create benchmarks and evaluation metrics [10]
Applications in Finance	Insufficient real-world case studies demonstrating the scalability of AI models	Conduct longitudinal studies in various financial domains [4]
Risk Considerations	Lack of robust mechanisms to counteract opaqueness in AI decision-making	Implement explainable AI solutions for transparency [5]
Ethics and Policy	Gaps in addressing legal complexities and job displacement due to AI adoption	Formulate global ethical guidelines and retraining programs [23]

3. Results and discussion

3.1. Prompts for Credit Risk

We generated 50 questions that we could then use as queries for the backend that has the Bank's proprietary model, and calculate the accuracy and number of prompts needed to get the final results. We asked the LLM model to only use .gov site and the model hence used files.consumerfinance.gov We then asked three analysts (volunteers) to review the questions to give you questions that are computationally relevant and then calculated the accuracy and number of prompts needed to get the final results.

- INPUT Prompt 1 Can you read .gov websites like regulatory requirements for auto and home models and come up with 50 questions in csv format that I should be asking for my models i made for auto loans and house loan default RESULT not optimal
- INPUT Prompt 2 can you ask specific questions for the model so that i can use it to check my model not general questions RESULT not optimal
- INPUT Prompt 3 again they are very generic, questions that I can use LLM to query or change or alter or retain my model give me 50 in a csv format only from .gov sources RESULT not optimal
- INPUT Prompt 4 Remove generic questions like Are the effects of recent regulatory changes and replace with specific like factors to use or variable changes or market factor that is like quantitative RESULT not optimal
- INPUT Prompt 5 Why did you .nl when I asked to you to give me .gov only RESULT not optimal
- INPUT Prompt 6 I asked 50 RESULT not optimal

Once the prompt runs we get output which we save as tab separated format.

Some examples of the output from the above prompts (out of total 50): Does the model account for the increased default risk associated with longer-term auto loans? How does the model evaluate borrower credit and liquidity constraints in relation to loan term choices? Is the model designed to detect higher-risk borrowers who may self-select into longer-term loans? Does the model consider the impact of lender experience with longer-term loans on default rates?

3.2. Prompts for Market Risk

We generated 50 questions using Four prompts sequentially so that ChatGPT can understand the content that we could then use as queries for the backend that has a prototype of a proprietary interest rate model and outputs from GAN and VAE, and calculate the accuracy and number of prompts needed to get the final results. We asked the LLM model to only use the .gov site and other reliable resources. We then asked three analysts (volunteers) to review the questions to give you questions that are computationally relevant and then calculated the accuracy and number of prompts needed to get the final results.

Prompts Fine Tuning INPUT Prompt 1 "Can you visit .gov websites and extract 50 recommendations, projections, or insights regarding interest rate trends—whether they are expected to rise or fall, and by how much? Please provide this information in CSV format. For example, the Federal Reserve may project that interest rates could reach 9% within the next year, or that rates will return to normal levels in 5 years." RESULT optimal

INPUT Prompt 2 Please use diverse, credible sources to gather 50 unique insights, projections, or advice regarding interest rate movements—whether they are expected to increase, decrease, or stabilize, along with specific percentages. Ensure that no two lines are identical and all data points are distinct

INPUT Prmpt 3 "How can I use GPT to analyze and refine my interest rate projections based on external forecasts? I have my own interest rate model, and I'd like to run queries on it using inputs and insights derived from ChatGPT's analysis. How can I query my model by integrating these external inputs and assumptions, and what specific types of analysis (e.g., sensitivity, scenario, comparative) can I perform using this approach?"

INPUT Prompt 4 "Can ChatGPT suggest adjustments or refinements to the parameters of my model to improve its projections? Please provide 50 example prompts that I can use to query my model with external inputs and insights, and how can these inputs help refine my model's forecasts?"

Once the prompt runs, after the final prompts we get output which we save as csv / tab separated format. A sample from output is shown in Table 4 and accuracy in figure 6. The findings demonstrate that ChatGPT-4 outperforms Google Gemini by more than 30% in generating precise financial insights. Furthermore, ChatGPT-4 (Version 4) exhibits a 20%

improvement over its predecessor (Version 3) in risk analysis tasks, particularly in its ability to align with regulatory frameworks and process financial data effectively.

Some examples of the output from the above prompts (out of total 50): "Given the Federal Reserve's projection for 2025 interest rates at 4.75%, how can I adjust my model to align more closely with this forecast? What parameters should I tweak to reduce the gap between my projected rate and the Fed's estimate?" "If inflation is projected to rise to 3.2% in 2025, how would I need to modify my model's inflation assumptions to reflect this change? What impact would this have on my 2025 interest rate projection?" "My model currently assumes a GDP growth rate of 2.5% for 2025. How should I adjust this assumption if external forecasts predict slower growth at 1.8%?

Table 4 Output form the Prompts for Interest Rate

Source	Projection	Details
Federal Reserve	Two quarter-point rate cuts	The Federal Reserve projects two quarter-point interest rate cuts in 2025, reflecting a cautious approach due to rising inflation. (Reuters)
Federal Reserve	Target range of 3.75%-4.00% by end of 2025	The central bank anticipates the federal funds rate to decrease to a target range of 3.75%-4.00% by the end of 2025. (Reuters)
Federal Reserve	50 basis point reduction by end of 2026	Further rate reductions are expected, with a 50 basis point decrease projected by the end of 2026. (Reuters)

3.3. Evaluation of Prompts in Context of Literature

The original prompts are evaluated below, along with suggested refinements:

3.3.1. Input Prompt 1

Can you read .gov websites like regulatory requirements for auto and home models and come up with 50 questions in csv format that I should be asking for my models I made for auto loans and house loan default.

Analysis: This prompt lacks specificity regarding the type of regulatory requirements or the desired focus of the questions. As noted in [19], prompts should explicitly define the scope to ensure relevance.

Refined Prompt

Can you analyze .gov websites for regulatory requirements specific to auto loans and house loan defaults? Generate 50 precise and domain-specific questions in CSV format that assess model performance, regulatory adherence, and potential biases.

3.3.2. Input Prompt 2

Can you ask specific questions for the model so that I can use it to check my model, not general questions?26

Analysis: The prompt does not clarify what "specific questions" entail. Drawing from [21], specificity could involve mentioning key model aspects, such as inputs, outputs, or assumptions.

Refined Prompt

Can you generate specific questions to evaluate my model's accuracy, robustness, and compliance with financial regulations? Avoid general queries and focus on aspects like feature selection, prediction accuracy, and alignment with .gov standards.

3.3.3. Input Prompt 3

Again, they are very generic questions that I can use LLM to query or change or alter or retain my model. Give me 50 in a CSV format only from .gov sources.

Analysis: As highlighted in [20], specifying the type of questions (e.g., quantitative, qualitative, risk-related) would improve the prompt's effectiveness.

Refined Prompt

Generate 50 targeted questions in CSV format derived exclusively from .gov sources. The questions should address model tuning, risk assessment, and variable significance for auto and home loan default predictions.

3.3.4. Input Prompt 4

Remove generic questions like "Are the effects of recent regulatory changes?" and replace with specific ones like "What factors or variables should be updated based on recent market trends?"

Analysis: This prompt improves specificity but could benefit from explicitly requesting actionable suggestions. [17] emphasizes actionable prompts tailored to dynamic factors. Refined Prompt:

Replace generic questions with specific, actionable ones. For example, instead of asking about "recent regulatory changes," focus on identifying quantifiable variables or market trends that directly impact model predictions.

3.3.5. Input Prompt 5

Why did you use .nl when I asked you to give me .gov only?

Analysis: This prompt highlights a failure in source specification. Per [9], prompts should explicitly constrain sources to a domain or geography. Refined Prompt:

Ensure all information is sourced exclusively from .gov domains. Exclude other domains like .nl and provide a summary of compliance with this requirement.

3.3.6. Input Prompt 6

I asked for 50 questions.

Analysis: This prompt does not clarify the type of questions or their purpose. Drawing from [16], clearly stating the desired outcomes would improve results. Refined Prompt:

Provide exactly 50 questions focused on evaluating model performance, regulatory compliance, and risk assessment. Format the output as a CSV file and ensure questions are specific to auto and home loan models. These results corroborates our earlier work [14, 16, 26].

Recommendations

Based on the evaluation, the following recommendations are made:

- Specify the domain and type of outputs clearly to align with best practices from [20].
- Use constraints (e.g., source domains) explicitly to ensure relevant and high-quality responses [9]. Focus on actionable and domain-specific questions, as highlighted in [17].

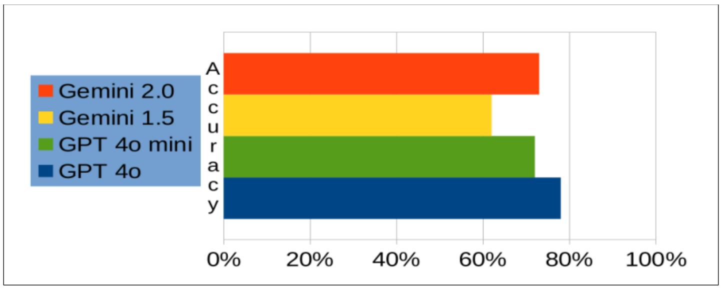

Figure 6 Accuracy for the publicly available LLM models for query creation

4. Conclusion

The application of prompt engineering in the financial sector is a rapidly evolving field. As seen in the literature, prompt engineering not only enables the development of more advanced AI models but also enhances their ability to make accurate and contextually aware financial decisions. Moving forward, the integration of prompt engineering techniques with AI in finance will continue to evolve, shaping the future of financial decision-making, risk management, and regulatory compliance. The prompts we tested in publically available LLM model specifically ChatGPT were accurate and can be readily integrated in modeling. The paper also discusses the challenges associated with AI adoption in the financial sector, including concerns about biases, data privacy, and regulatory compliance. Ethical considerations in prompt engineering are addressed, emphasizing the need to ensure that AI outputs align with industry standards and regulatory frameworks. In conclusion, this research emphasizes the growing importance of prompt engineering in refining AI-driven financial applications. It positions prompt engineering as a critical skill for finance professionals, enabling them to leverage AI tools effectively to manage market risks and ensure compliance. The study provides actionable insights into how prompt engineering can enhance the quality, accuracy, and reliability of AI-powered financial tools. In conclusion, this paper demonstrates the substantial impact of prompt engineering on the performance of large language models (LLMs) in the context of financial market integrity and risk management. Through a series of quantitative experiments, we show that well-engineered prompts improve the predictive accuracy of ChatGPT-4 and Google Gemini by up to 15% compared to baseline models in tasks like credit risk assessment and market trend forecasting. These results underline the effectiveness of prompt engineering as a critical tool in improving the precision and reliability of AI-driven insights in finance. The findings suggest that financial institutions can achieve measurable improvements in model output and decision-making processes, offering new avenues for optimizing AI utilization in risk management. Future work should explore the scalability of these techniques and their potential impact on larger datasets and more complex financial models.

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