# Applying Large Language Models (ChatGPT) In Inventory Management Within Supply Chain Management


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## DEDICATION

Dedicated to my Late Mother, Mrs. Sholape Agbi.

*"Bring your brush*

*to this canvas"*

Oriname Agbi

**DECLARATION**

I, Oriname Agbi (22139986) hereby declare that I have produced the work presented in this dissertation during the scheduled study period. I also declare that I have not taken any material from any source except referred to wherever due that amount of plagiarism is within an acceptable range.

Date: September, 2023

Oriname Agbi

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## ABSTRACT

In the evolving landscape of global business, inventory management has emerged as a cornerstone of supply chain dynamics. Historically grounded in deterministic models, the complexities introduced by globalization and intricate supplier networks have necessitated a fresh approach to inventory strategies. This dissertation explores the transformative potential of Large Language Models (LLMs), with a particular focus on ChatGPT, as a solution to modern challenges in inventory management.

Through an exhaustive literature review, the research identifies the shortcomings of traditional models in today's intricate business environment. It underscores the promise held by LLMs, such as ChatGPT, in offering advanced predictive analytics and fostering real-time, intelligent interactions. Central to this study is the introduction of a novel framework, built around OpenAI's ChatGPT-3.5. This framework aims to marry the capabilities of LLMs with the multifaceted demands of contemporary inventory management.

Adopting a mixed-method approach, the research critically evaluates the efficacy and applicability of the proposed framework. Preliminary findings suggest that while ChatGPT holds significant promise in areas like demand forecasting and stock optimization, its integration comes with its own set of challenges.

This study stands as a dual contribution: academically, it enriches the discourse on LLM applications in supply chain management; practically, it offers actionable insights for

industry professionals. In conclusion, the research emphasizes the need for a harmonious relationship between LLMs and human expertise, advocating for an integration strategy that is both technologically advanced and human-centric in its approach.

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# Chapter One

# Introduction

## 1.1 Overview of Research

Inventory management, while traditionally perceived as a mere logistical function, has evolved into the crux of supply chain dynamics in the modern business landscape. At its heart, it involves achieving the optimal balance between supply and demand, ensuring that businesses neither overstock nor run short, thus optimizing operational efficiency. This balance has conventionally been maintained using deterministic models like the Economic Order Quantity (EOQ) model, rooted deeply in historical data [1].

However, the face of global business has undergone a paradigm shift. With globalization, companies are now operating within expansive, multi-tiered supplier networks that stretch across continents. The complexity introduced by these networks, combined with the unpredictability of ever-shifting consumer behaviors and market trends, poses significant challenges. Adding to this complexity are unforeseen 21st-century challenges, ranging from global pandemics to geopolitical shifts, which can disrupt even the most streamlined supply chains [2].

While traditional models like EOQ provide foundational guidance, they increasingly show their limitations in this intricate and dynamic environment. The repercussions of these limitations can be dire for businesses, from stockouts leading to eroded customer trust, to excessive holding costs that diminish profitability.

In light of these challenges, the integration of Machine Learning (ML) and Artificial Intelligence (AI) into inventory management is no longer just a futuristic vision but a pressing necessity. These technologies offer the promise of predictive analytics, capable of forecasting demand with a higher degree of accuracy by analyzing vast and varied datasets [3]. Furthermore, the advent of Large Language Models (LLMs) like ChatGPT brings forth the potential to revolutionize supply chain communications, facilitating real-time, intelligent interactions and decision-making processes[4].

The application of AI and ML in inventory management doesn't just offer incremental improvements; it can lead to transformative changes in how supply chains operate. Such systems can self-learn, adapt, and provide actionable insights, making them indispensable in navigating the complexities of contemporary supply chains.

This dissertation delves deep into the potential of applying LLMs, specifically ChatGPT, in reshaping inventory management within the broader realm of supply chain management. As businesses grapple with the evolving challenges of a globalized world, embracing the capabilities of advanced AI models may well be the key to unlocking unprecedented levels of efficiency and responsiveness in their supply chains.

## 1.2 Problem Statement

The transformative potential of LLMs in the realm of inventory management is clear. Yet, there exists a glaring gap. Comprehensive, systematic research that delves into the integration of LLMs within the supply chain remains sparse. This study embarks on a journey to bridge this chasm. At its heart, the research aims to sculpt a novel framework, with a keen focus on OpenAI ChatGPT-3.5, intertwining the capabilities of LLMs with the intricate needs of inventory management[5].

## 1.3 Research Questions

This research seeks to answer several pressing questions:

1. Demand Forecasting: How might LLMs, like ChatGPT, redefine demand forecasting in inventory management by synthesizing historical sales data with broader market trends?

2. Optimal Stock Levels: Can insights driven by LLMs recalibrate the way businesses perceive optimal stock levels, especially when juggling variables like lead time, demand fluctuations, and service level objectives?

3. Returns Management: How could ChatGPT revolutionize returns management, diving deep into return reasons, and offering strategies for mitigation?

4. Lead Time Variability: In the face of fluctuating lead times, how might LLMs serve as a beacon, predicting potential pitfalls and offering strategies for mitigation based on historical data trends?

5. Inventory Valuation: Could ChatGPT be the tool businesses need for real-time inventory valuation, seamlessly factoring in variables like purchase costs, holding overheads, and looming obsolescence costs?

6. Supplier Relationship Management: How might ChatGPT redefine supplier relationship management, offering a deep dive into supplier data and performance metrics to craft data-driven strategies?

## 1.4 Research Objectives

1. The primary objectives of this research are:

2. To conceptualize and design a framework that synergizes LLM capabilities with inventory management needs.

3. To develop a proof-of-concept chatbot that showcases the practical application of this framework.

4. To evaluate the efficacy and feasibility of the proposed solution in real-world supply chain scenarios.

## 1.5 Purpose of the Study

This study aims to investigate the potential of Large Language Model like ChatGPT in enhancing inventory management within the supply chain domain. Specifically, the research will delve into how ChatGPT can be applied to inventory management to improve decision-making and operational efficiency. By doing this, the study will offer a structured methodology for integrating LLMs into existing inventory management systems. To ascertain the effectiveness of LLMs in this domain, this research poses the following hypothesis.

## 1.6 Research Hypothesis

The research hypothesis asserts that applying a large language model like ChatGPT to inventory management can improve the efficiency and accuracy of inventory control processes significantly compared to traditional techniques. Specifically, it is hypothesized that a large language model like ChatGPT-based system can provide more accurate demand forecasts and optimize inventory levels in the retail sector.

## 1.7 Significance of the Study

This study holds potential significance in contributing to the emerging field of LLM applications in supply chain management, particularly inventory management [6] . By offering a detailed analysis of potential benefits, practical applications, and challenges of using ChatGPT, this research could guide industry professionals in optimizing their inventory management operations. Furthermore, the study could pave the way for more accurate, efficient, and responsive inventory control in retail, thereby enhancing operational efficiency and customer satisfaction.

On top of its practical implications, the study also has the potential to contribute to academic knowledge. By investigating a relatively unexplored area, the research could fill a significant gap in the literature and provide a foundation for future studies on the application of LLMs in retail inventory management.

As the application of ChatGPT and other large language models in supply chain management, particularly inventory management, is still a developing field, this study's findings and methodologies could serve as a reference point for researchers and scholars interested in exploring the potential of LLMs in other aspects of inventory control or in different industries.

## 1.8 Research Methodology

For this research, I must adopt quantitative and qualitative data as a mixed method in order to analyze the research questions in a well-defined manner. Quantitative research is necessary for implementing the proposed model in real-life scenarios and provides an excellent way of finalizing results after statistical analysis. Moreover, qualitative research is required to collect the data from the literature.

## 1.9 Ethical Consideration

The ethical consideration is as follows.

- This study will utilize the original dataset from the UCI repository and will
- not include any biased samples.
- We will acknowledge the research community when we use material from
- other sources in the dissertation.
- We will add authentic results to the dissertation.

## 1.10 Dissertation Structure

The study will be structured into several key sections, each fulfilling a critical role in the overall research. Following this introduction, a comprehensive literature review will be conducted to lay a theoretical foundation for the study. The literature review will critically analyse the current state of knowledge in the field, spotlight gaps in the existing research, and identify potential areas for further exploration. Next, the research methodology will be delineated, offering details about the approach and methods utilized to gather and analyse data. This section will describe the creation of a structured methodology for integrating ChatGPT into existing inventory management systems, with an emphasis on data ingestion, model training, output generation, and system evaluation.

This will be followed by the presentation and discussion of the research findings, which will offer insights into the application of ChatGPT in retail inventory management and its potential benefits and challenges. The findings will provide both quantitative and qualitative evaluation of the effectiveness of ChatGPT in inventory management, as well as insights into the practical issues faced during implementation.

Finally, the study will conclude with a summary of the key findings, implications for practice, and recommendations for future research. This conclusion will also reflect on the end-to-end lifecycle of applying ChatGPT to inventory management, from data ingestion to user-facing output. This structure will ensure a logical and coherent flow of ideas throughout the study, enhancing its comprehensibility and usability [**empty citation**].

# Chapter Two

# Preliminary Studies

## 2.1 Introduction to Large Language Models (LLMs)

In the ever-evolving landscape of artificial intelligence (AI), Large Language Models, commonly referred to as LLMs, have emerged as a transformative force, pushing the boundaries of what machines can comprehend and articulate. At their core, LLMs are designed to mimic human-like linguistic abilities. Unlike rudimentary text generators, they delve deep into the intricacies of language, capturing nuances, context, and even cultural references [7].

These advanced models are the outcome of training on colossal datasets, often encompassing vast swaths of the internet, from articles and books to websites and forums. This extensive training allows them to have an incredibly broad knowledge base, making them adept at understanding a wide array of topics and contexts. The sheer volume of data they're exposed to means that they don't just parrot back information; they generate text that feels organic, contextual, and eerily human-like.

The potential of LLMs extends far beyond simple text generation. Their proficiency in context comprehension means they can be utilized in tasks that require understanding of underlying sentiments, intentions, or emotions in textual data. This has led to a myriad of applications, from chatbots and customer service automations to aiding researchers in synthesizing vast amounts of literature.

Moreover, the rise of LLMs has heralded a shift in the AI paradigm. Previously, AI models were highly specialized, designed for specific tasks. LLMs, on the other hand, offer a more generalized approach. With their expansive training, they can be fine-tuned to specific applications without the need for extensive retraining. This flexibility, combined with their linguistic prowess, positions LLMs as not just another tool in the AI arsenal, but as a pivotal advancement that could redefine human-machine interactions.

In the subsequent sections, we will delve deeper into the mechanics of LLMs, their applications, and the potential they hold for industries, with a particular focus on their role in inventory management within supply chain systems.

## 2.2 Evolution of LLMs in Inventory Management

Inventory management stands as one of the most crucial components within the broader framework of supply chain management. Historically, it has been guided by quantitative data — from stock levels to sales predictions. Decision-makers relied heavily on past sales figures, storage costs, lead times, and various deterministic models to manage and forecast inventory needs [8].

However, the modern business environment, with its dynamic market trends and consumer behaviors, demands a more nuanced approach. Large Language Models (LLMs) present a promising avenue in this regard. These sophisticated models, trained on extensive textual datasets, can provide insights beyond the purview of traditional numerical data.

For instance, a traditional inventory management system might rely on sales figures from the previous year to forecast the next year's demand. In contrast, an LLM could factor in recent customer feedback, market sentiment from social media, and even global trends, offering a more holistic view of potential inventory needs. This is especially pivotal in scenarios where there might be sudden surges or drops in demand, often triggered by factors that aren't purely transactional. A positive product review going viral, a celebrity endorsement, or even geopolitical events can influence demand, and LLMs are adept at capturing these subtleties.

Moreover, in the realm of supplier relationship management, LLMs can bring a transformative change. Beyond just evaluating delivery times and defect rates, these models can analyze the nuances in supplier communications, feedback, and even sentiments, offering insights into potential collaboration opportunities or challenges.

The integration of LLMs specifically into inventory management signifies a monumental shift from static, historical data-driven decisions to a more dynamic, adaptive, and context-aware approach. By combining the strengths of both traditional forecasting methods and the qualitative insights offered by LLMs, businesses can achieve a more refined, responsive, and efficient inventory management system, ensuring they're always a step ahead in meeting market demands.

## 2.3 The Role of ChatGPT in Inventory Management

The intricate realm of supply chain management, inventory management remains a cornerstone, ensuring that products are available at the right place, at the right time, and in the right quantity. To optimize this delicate balance, innovations like ChatGPT, a prominent instance of Large Language Models, are making significant inroads [9].

**Demand Forecasting:** One of the perennial challenges in inventory management is accurately predicting future demand. Traditional models rely heavily on historical data, which, while valuable, often fall short in capturing sudden market shifts. ChatGPT, with its capacity to analyze vast amounts of textual data, brings a fresh perspective. For instance, it can scrutinize product reviews to gauge customer sentiment, assess feedback to identify product improvements or shortcomings, and even monitor broader market trends or news that might impact demand.

By collating and analyzing this information, ChatGPT can offer forecasts that are not only data-driven but also context-aware, ensuring businesses remain agile and responsive to market fluctuations.

**Revolutionizing Supplier Interactions:** Efficient communication with suppliers is pivotal for seamless inventory management. ChatGPT can be harnessed to automate various aspects of supplier interactions, from placing orders and confirming delivery dates to conducting quality checks and even handling grievances. Such automation not only streamlines operations but also minimizes human errors, ensuring that the inventory process is more consistent and reliable[10].

**Enhancing Real-time Customer Support:** Today's consumers demand swift and accurate responses to their queries. In the context of inventory, this could range from questions about product availability to delivery timelines. Integrating ChatGPT into customer support systems can ensure that customers receive instant, accurate answers to their inventory-related questions. This not only enhances the customer experience but also reduces the operational burden on human customer service representatives, allowing them to focus on more complex queries [11].

In essence, ChatGPT's capabilities extend far beyond just text generation. When applied judiciously within inventory management, it promises a paradigm shift — one where decisions are more informed, operations more streamlined, and customer interactions more efficient and engaging. The potential impact on profitability, customer satisfaction, and overall operational efficiency cannot be overstated.

## 2.4 LLMs vs. Traditional Models in Inventory Management

Inventory management has historically been anchored in traditional models that utilize deterministic data, offering structured and formulaic approaches to stock control. Among these, the Economic Order Quantity (EOQ) stands out as a prime example[1]. EOQ, with its mathematical precision, provides guidelines on order quantities by balancing ordering costs with holding costs, all based on historical data and sales patterns. While these models have been the backbone of inventory management for decades, the rapidly evolving business landscape is highlighting their inherent limitations [12].

Enter Large Language Models (LLMs), like ChatGPT, which promise a paradigm shift in how inventory decisions are made. Unlike deterministic models, LLMs can ingest, process, and interpret vast amounts of textual data, providing a richer, more dynamic basis for decision-making [13].

**Holistic Data Analysis:** While traditional models like EOQ draw conclusions based solely on past sales and established patterns, LLMs can delve deeper. They can analyze textual data such as customer feedback, product reviews, supplier communications, and even global market sentiments. This ability to factor in qualitative insights along with quantitative data gives LLMs a distinct edge [14].

**Adaptive Forecasting:** One of the inherent limitations of deterministic models is their reliance on past patterns, making them less adaptive to sudden market changes. LLMs, on the other hand, can quickly adapt their recommendations based on real-time data. For instance, if a product receives a surge of negative reviews, ChatGPT can factor this into its demand forecast, potentially suggesting a reduction in order quantities even if past sales data might indicate otherwise.

**Incorporating External Factors:** The modern business environment is influenced by a myriad of external factors, from geopolitical events to cultural trends. While traditional models may struggle to account for these, LLMs can parse news articles, social media trends, and more to gauge their potential impact on inventory decisions.

However, it's crucial to note that the transition from traditional to LLM-based inventory management isn't about replacing one with the other. Instead, it's about achieving a harmonious blend. The deterministic insights from models like EOQ provide a stable foundation, while the dynamic capabilities of LLMs introduce flexibility and adaptability. In essence, the fusion of these approaches promises a more resilient, responsive, and efficient inventory management system for the modern age.

## 2.5 Challenges and Considerations

The integration of advanced technologies like Large Language Models (LLMs) into inventory management, while promising, is not without its complexities. ChatGPT, as an exemplar of LLMs, has shown significant potential in various applications, but the path to seamless integration in inventory management requires careful navigation of challenges and considerations.

**Computational Demands:** One of the foremost challenges in deploying LLMs like

ChatGPT in inventory management is the sheer computational power required. Training these models necessitates vast datasets and immense processing capabilities, often requiring specialized hardware infrastructure. For many businesses, especially smaller ones, the initial investment in such computational resources can be prohibitive. Moreover, the continuous updating and fine-tuning of these models to ensure their relevance and accuracy further intensify these demands [15].

**The "Black Box" Dilemma:** LLMs, for all their prowess, remain enigmatic in their decision-making processes. The intricate neural networks that underpin models like ChatGPT make it challenging to pinpoint the exact rationale behind their outputs. In the nuanced and often high-stakes world of inventory management, where decisions can have cascading impacts on supply chains, profits, and customer satisfaction, this lack of transparency can be problematic. Blindly trusting model recommendations without understanding their basis can lead to unforeseen complications or missed opportunities [16].

**Ensuring Checks and Balances:** Given the above challenges, it becomes imperative to have robust checks and balances in place. While ChatGPT can be an invaluable assistant, human oversight remains essential, especially for critical inventory decisions. This dual approach ensures that while businesses can leverage the speed and data-processing capabilities of LLMs, they also benefit from the intuition, experience, and contextual understanding that human professionals bring to the table [17]

**Data Sensitivity and Bias:** Another pivotal consideration is the data used to train these models. If the training data reflects certain biases or inaccuracies, the model's outputs will inherently carry those biases forward. In the context of inventory management, this could lead to skewed demand forecasts or misinterpretations of market sentiment [18].

While LLMs like ChatGPT herald a new era of data-driven decision-making in inventory management, their integration should be approached with a blend of enthusiasm and caution. By acknowledging the challenges, investing in the necessary infrastructure, and ensuring human oversight, businesses can harness the full potential of these models while mitigating associated risks.

## 2.6 Future Prospects of ChatGPT in Supply Chains

The evolution of technology and artificial intelligence paints a promising picture for the future of supply chain management, with ChatGPT poised to play a pivotal role [19]. As the boundaries of what's possible continue to expand, there are several emerging trends and developments that suggest a transformative impact on how inventory management systems operate and evolve.

**Integration with IoT:** The Internet of Things (IoT) is rapidly transforming the way businesses operate, connecting physical assets to digital networks. In the context of supply chains, smart devices and sensors could relay real-time data about stock levels, warehouse conditions, or transportation status directly to ChatGPT. This instantaneous flow of information can empower the LLM to make quicker and more informed decisions, dynamically adjusting to changing circumstances[19].

**Edge Computing Synergy:** With the growth of edge computing, data processing capabilities are being pushed closer to the source of data generation. This means that instead of sending all data to centralized data centers for processing, much of it can be analyzed on-site, in real-time. When combined with ChatGPT's capabilities, this can lead to ultra-responsive inventory systems that react instantaneously to shifts in demand, supply disruptions, or logistical challenges.

**Enhanced Predictive Capabilities:** As ChatGPT and similar LLMs continue to evolve, their predictive modeling capacities are likely to become even more refined. Beyond just analyzing textual data, future iterations might incorporate a broader range of data types, including video and audio, to forecast inventory needs 2023chatgpt. For example, sentiment analysis from customer service calls could offer additional layers of insights into potential demand surges or dips.

**Holistic Supply Chain Optimization:** The potential applications of ChatGPT extend beyond just inventory management. In the future, it could play a role in broader supply chain optimization tasks, from supplier negotiations based on global market sentiments to dynamic routing of shipments based on real-time logistical data [14].

**Sustainability and Ethical Decision Making:** As businesses globally grapple with the imperative of sustainable operations, LLMs could be instrumental in guiding eco-friendly supply chain decisions. By analyzing data related to carbon footprints, waste generation, and sustainable sourcing, ChatGPT could recommend inventory practices that align with environmental and ethical goals.

In essence, the horizon of possibilities with ChatGPT in supply chains is vast and ever-expanding. As businesses gear up for the challenges and opportunities of the future, the fusion of cutting-edge technology with advanced LLMs like ChatGPT promises a supply chain ecosystem that's not just efficient and resilient but also aligned with the evolving needs and values of the modern world.

## 2.7 Chapter Summary

This chapter delved into the rise of Large Language Models, focusing on ChatGPT and its potential applications in inventory management within supply chain systems. The benefits, challenges, and future prospects of incorporating LLMs in this domain were explored. The following chapter will review existing literature on this convergence of LLMs and supply chain management.

# Chapter Three

# Literature Review

## 3.1 Overview of Research

In the contemporary era, marked by rapid technological advancements, the integration of traditional sectors with state-of-the-art computational methods is becoming increasingly prevalent. A leader in this transformative wave is the emergence and dominance of Large Language Models (LLMs), which have started to carve a niche for themselves across diverse industries. Among these, supply chain management—a cornerstone of global commerce—is grappling with the myriad possibilities and challenges posed by LLMs.

## 3.2 Introduction to the Role of LLMs in Supply Chain Management

Supply chain management, with its intricate network of suppliers, customers, and service providers, has historically faced complex decision-making challenges. Traditional methods often fell short of providing clear, lucid interpretations of optimization outcomes, especially when myriad stakeholders were involved. This is where LLMs, with their unparalleled computational capabilities and human-like language processing, are making a mark. By bridging the gap between complex automation processes and human understanding, LLMs are heralding a new era in supply chain management.

## 3.3 Main Applications of LLMs in Supply Chain

Guilherme Francisco Frederico's [20] exploration into the realm of ChatGPT and its implications for supply chain management stands as a cornerstone in understanding the evolving dynamics of this industry. By delving deep into the nuances of how LLMs, particularly ChatGPT, can be integrated into supply chain operations, Frederico opens up a world of possibilities that were hitherto either unexplored or underutilized.

One of the most salient applications Frederico [20]highlights is the potential of ChatGPT in route optimization. In traditional supply chain operations, determining the most efficient route, especially in complex multi-modal logistics scenarios, often required extensive computational resources and human expertise. Frederico posits that with ChatGPT, this process can be significantly expedited. The model can analyze vast datasets, incorporating real-time variables such as weather patterns, traffic conditions, and geopolitical events, to suggest optimal routes. This not only ensures timely delivery but also translates to substantial fuel savings and reduced carbon footprints, aligning with the global push towards sustainable operations.

Another transformative application lies in predictive maintenance. The age-old adage "prevention is better than cure" holds especially true in supply chain management, where equipment downtimes can result in cascading delays and financial losses. ChatGPT, with its ability to process and learn from historical maintenance records, sensor data, and user feedback, can predict potential equipment failures or maintenance requirements. By doing so, it allows businesses to transition from reactive to proactive maintenance schedules, ensuring continuity in operations and reducing unforeseen expenses.

Frederico [20]also delves into the realm of order shipments. In an increasingly digital world, where customers demand real-time updates and swift deliveries, the traditional methods of order processing often fall short. ChatGPT, with its sophisticated algorithms, can streamline this process. From automating order entries based on customer interactions to dynamically allocating inventory based on demand predictions, the model promises to reduce lead times and enhance customer satisfaction.

The potential of ChatGPT in enhancing stakeholder relationships cannot be overstated. In a domain where communication with suppliers, partners, and customers is paramount, ChatGPT can serve as an intermediary, ensuring seamless interactions. Be it automating routine communications, providing instant responses to stakeholder queries, or even predicting potential areas of contention and proactively addressing them, ChatGPT promises to foster stronger, more transparent relationships.

Another pivotal application Frederico [20]underscores is in the realm of data analysis. Modern supply chains are inundated with data— from inventory levels and sales forecasts to customer feedback and supplier performance metrics. Analysing this data manually or even with traditional computational methods is not just time-consuming but also prone to oversights. ChatGPT, with its unparalleled processing capabilities, can swiftly analyse these vast datasets, drawing insights that might escape even the most trained human eye. Whether it's identifying purchasing trends, predicting seasonal demand fluctuations, or even analysing supplier performance to renegotiate contracts, the model promises a level of data-driven decision-making that was previously unattainable.

In sum, Frederico's [20] exploration into ChatGPT's applications paints a picture of a future where supply chain operations are not just efficient but also intelligent. These interventions, as Frederico posits, hold the potential to usher in not just cost efficiencies but a paradigm shift in how supply chain management is perceived and executed. By weaving in LLMs into its fabric, supply chains can transition from being mere logistical operations to dynamic, responsive, and intelligent ecosystems that constantly adapt and evolve in response to external stimuli.

In the ever-evolving landscape of supply chain management, Li et al.'s [6]contribution to the discourse through their work "Large Language Models for Supply Chain Optimization" is both timely and revolutionary. At the heart of their research lies the OptiGuide framework—a tool that exemplifies the perfect amalgamation of sophisticated computation and user-friendly interfacing.

The genesis of OptiGuide [6]is rooted in a pressing challenge faced by supply chain stakeholders: the ability to comprehend and interpret complex optimization results. As supply chains have grown in complexity, the resultant data and analyses have become increasingly intricate. This often creates a chasm between the computational results and the stakeholders, many of whom might not have extensive technical expertise. OptiGuide, with its emphasis on processing plain language queries, is designed to bridge this gap. By allowing users to pose questions in natural language and receive insights in a similarly comprehensible format, the framework democratizes access to intricate data analytics.

But OptiGuide [6]is not just about simplification; it's about fostering trust and comprehension. In traditional supply chain operations, decisions based on computational models often met resistance owing to a lack of understanding or trust in the system's recommendations. By providing stakeholders with the ability to interact with the system, ask questions, and receive clear explanations, OptiGuide aims to build confidence in the optimization results. This is not just beneficial from an operational standpoint, but also crucial in ensuring that strategic decisions, based on these results, are implemented smoothly and without friction.

Li et al. [6] don't just stop at introducing this groundbreaking framework; they take the reader on a journey of its real-world implications by exploring its application within Microsoft's cloud supply chain. In an environment where server placements and resource allocations are crucial, and the costs of inefficiencies can run into millions, the importance of optimal decision-making cannot be overstated. OptiGuide, as the authors elucidate, provides stakeholders with insights that are not just technically sound but also easily digestible. Whether it's understanding the implications of placing a server in one location over another or gauging the cost-benefit analysis of specific resource allocations, OptiGuide ensures that stakeholders are equipped with all the information they need, in a format they can understand.

Moreover, the case study serves as a testament to the framework's versatility. While the Microsoft cloud supply chain provides a specific context, the underlying challenges it faces—complex decision-making, the need for stakeholder comprehension, and the imperative for trust—are universal across supply chains. This suggests that the potential applications of OptiGuide could span a multitude of industries and scenarios.

In essence, Li et al.'s [6] introduction of the OptiGuide framework marks a paradigm shift in how we perceive the interface between humans and computational models in supply chain management. It's not just about harnessing the power of advanced computations; it's about ensuring that this power is accessible, understandable, and, most importantly, trusted by all stakeholders involved.

## 3.4 Literature Review Matrix

| **System Title** | **Lack(s)/Challenges** |
|---|---|
| ChatGPT in Supply Chains: Initial Evidence of Applications [20] | 1. Being initial evidence, the study might not cover the full range of ChatGPT applications in supply chains. 2. Potential challenges in scaling the applications across diverse supply chain setups. 3. Lack of long-term data to assess the sustainability and efficacy of the applications. 4. May not address the intricacies of integrating ChatGPT with legacy systems in supply chains. |
| Large Language Models for Supply Chain Optimization [6] | 1. Focus on optimization could mean a potential oversight of other aspects of supply chain management. 2. Potential issues in real-time adaptability and flexibility of the models during unforeseen supply chain disruptions. 3. The paper might primarily address the technical aspects, leaving out the human-centric challenges of integrating LLMs. 4. Challenges in ensuring data privacy and security when using LLMs for optimization in global supply chains. |

Table 3.1: Literature Review Matrix

## 3.5 Critical Analysis

In the realm of integrating Large Language Models (LLMs) within supply chain management, two notable works stand out. The first paper [20], "ChatGPT in Supply Chains: Initial Evidence of Applications," highlights the potential of ChatGPT in various facets of supply chain management, from route optimization to predictive maintenance. The emphasis is on the model's ability to analyze vast datasets, incorporating real-time variables, and ensuring timely delivery. Yet, the paper does underscore a critical limitation: while ChatGPT excels in data processing and adaptability, it cannot replace the nuanced decision-making innate to human experts.

The second paper [6], "Large Language Models for Supply Chain Optimization," introduces the OptiGuide framework—a tool that bridges the gap between complex automation processes and human understanding. The framework democratizes access to intricate data analytics by allowing stakeholders to pose questions in natural language. The case study involving Microsoft's cloud supply chain suggests the framework's potential versatility across different supply chain scenarios. However, the true universality of this tool, especially in diverse global supply chains with varied complexities, remains to be seen.

## 3.6 Outcome of the Review matrix

From the critical analysis of both papers, the following outcomes emerge:

- ChatGPT holds significant promise in supply chain operations, especially in route optimization, predictive maintenance, and stakeholder communications. Its ability to factor in real-time variables like traffic conditions and geopolitical events can expedite decision-making processes [20].

- However, there's a clear emphasis on the supplementary role of ChatGPT. It should bolster, not replace, human expertise, especially in nuanced decision-making scenarios.
- The OptiGuide framework, introduced by Li et al. [6], emphasizes the importance of bridging the technical-human divide. It seeks to make complex optimization results comprehensible to stakeholders.
- While the case study involving Microsoft's cloud supply chain is enlightening, the true potential of OptiGuide in diverse supply chain scenarios remains untested.

## 3.7 Limitations and Challenges

Yet, the journey of integrating LLMs into supply chain management is not devoid of challenges. Frederico's [6] research underscores that while ChatGPT excels in data processing and adaptability, it cannot supplant the nuanced critical thinking innate to humans. Instead, its role is envisioned as a supplementary tool that bolsters, rather than replaces, human decision-making. Further, as with any nascent technology, the broader implications of LLMs—especially in fields like supply chain management—remain an area ripe for exploration.

## 3.8 Implications and Future Directions

The dialogues surrounding LLMs, typified by works like those of Frederico [20] and Li et al. [6], accentuate the transformative potential of these models in reshaping supply chain management's very fabric. It's not just about streamlining processes; it's also about ensuring that these processes are human-centric, fostering comprehension, inclusivity, and shared growth. As LLMs like ChatGPT continue to meld with traditional sectors, the research by

Frederico and Li et al. emerges as a beacon, illuminating the present landscape and charting a path characterized by innovation and collaboration. As we stand at this technological crossroads, it's evident that the future of supply chain management is intertwined with the evolution of LLMs. And as these models continue to evolve, they beckon a future where technology and humanity coalesce seamlessly, where advancements aren't just about automation, but also about understanding and shared progress.

## 3.9 Chapter Summary

This chapter delved into the emerging literature on the role and potential of Large Language Models, particularly ChatGPT, in the domain of supply chain management. Two seminal works were critically analyzed, each presenting a unique perspective on how LLMs can reshape and enhance traditional supply chain operations.

While the promise of efficiency, adaptability, and enhanced stakeholder communication is evident, both papers also underscore the importance of human expertise. As the integration of LLMs in supply chains continues to evolve, the balance between automation and human intuition will be pivotal. The subsequent chapters will delve deeper into methodologies and potential practical applications, building on the foundational understanding established here.

# Chapter Four

# Research Methodology

## 4.1 Systematic Literature Review

A systematic literature review (SLR) has been employed to comprehensively assess the application of Large Language Models, specifically ChatGPT, within the domain of inventory management in supply chain management. Following established protocols, this SLR scrutinizes existing evidence impartially and repeatably. The methodology adopted for this study derives from the Kitchenham guidelines, esteemed in the domain of evidence-based software engineering, to conduct systematic mapping and reviews. This SLR centers on studies discussing the integration of LLMs, particularly ChatGPT, in supply chain management. The research methodology encapsulated in Figure 4.1 consists of three pivotal phases:

1. Planning the Review
2. Conducting the Review
3. Reporting the Review

### 4.1.1 Planning the Review

The process of initiating a Systematic Literature Review (SLR) is intricate and requires a robust blueprint to ensure that the review is comprehensive, unbiased, and systematic. Meticulous planning is paramount to guide the SLR from inception to completion and to guarantee that the review encompasses the entirety of the relevant literature available on the topic. The planning phase is composed of several pivotal steps, each of which is crucial for the success of the SLR:

**Formulating Research Questions** The foundation of any SLR lies in clearly defined research questions. These questions dictate the direction of the review and provide a roadmap for identifying relevant literature. It's essential that the research questions are concise yet inclusive enough to capture the essence of the topic under investigation.

**Identifying Suitable Repositories** Not all databases and repositories are created equal. Depending on the topic of the SLR, certain repositories might be more pertinent than others. Identifying and selecting the most suitable ones ensures that the literature sourced is relevant, recent, and rigorous. It also widens the search net, increasing the chances of capturing all essential articles and papers related to the topic.

**Crafting the Search String** The search string is the linchpin that determines the efficacy of the literature search. It should be crafted with precision, using relevant keywords and Boolean operators to ensure that the results are aligned with the research questions. A well-constructed search string minimizes the chances of overlooking significant studies.

**Defining Inclusion and Exclusion Criteria** To maintain the relevance and focus of the SLR, it's imperative to set clear criteria for which studies to include and which to exclude. These criteria ensure that the review remains targeted and prevents the inclusion of tangential or irrelevant studies. Clear criteria also add a layer of objectivity to the selection process.

**Establishing Quality Assessment Standards** To ensure the credibility of the SLR, the quality of the included studies must be assessed. This involves establishing a set of standards or benchmarks against which each study can be evaluated. By doing so, the review ensures that the findings and conclusions drawn are based on high-quality, credible sources.

In the succeeding sections, each of these activities will be elucidated in greater detail, providing a comprehensive understanding of the planning phase of the SLR.

### 4.1.2 Research Questions

Following the establishment of our research questions, we selected appropriate data repositories to source pertinent studies. Our choice of digital repositories was influenced by the regularity of relevant publications within each database and the specific keywords selected for our topic. **RQ1:** How are Large Language Models being integrated into inventory management within supply chain management? **RQ2:** What potential advantages and challenges have been identified in using ChatGPT for inventory management?

### 4.1.3 Online Databases

To collate a relevant set of primary studies, prominent digital libraries have been chosen, encompassing journals and conferences. Four prominent databases were selected: IEEE Xplore, Science Direct, Web of Science, and Google Scholar. The results from these databases are summarized in Table 4.1.

Table 4.1: Online Databases

| No | Database | Initial result |
|---|---|---|
| 1 | IEEE Xplore | 146 |
| 2 | Science Direct | 390 |
| 3 | Google Scholar | 456 |
| 4 | Web of Science | 319 |
| **Total** | | 1311 |

### 4.1.4 Search String

Crafting an effective search string is pivotal to obtaining studies that align closely with the research objectives. Given the research's focus on Large Language Models, particularly ChatGPT, and their applications in inventory management within supply chain management, our search string was designed to capture the essence of these topics.

To build a robust search string, the following steps, inspired by the guidelines of Afzal et al. [21], were undertaken:

1. Identification of the Primary Concept: The crux of our research revolves around the interplay of Large Language Models, specifically ChatGPT, within the context of inventory and supply chain management. Thus, the foundational concept was established around these terms.

2. Defining Alternative Terms: Recognizing that different authors might employ varied terminologies to discuss similar concepts, a range of alternative terms were identified. For instance, while some might refer to "Large Language Models," others might use "LLMs" or "Advanced Textual Models."

3. Employing Boolean Operators: To enhance the precision and scope of the search,

Boolean operators were utilized. The operator OR was used to encompass alternative words and synonyms, ensuring that all relevant literature, irrespective of the specific terminology used, was captured. The AND operator was used to ensure that the retrieved articles discussed both the concepts of LLMs (or ChatGPT) and inventory management within supply chain domains.

The resultant search string resembled: (Large Language Models OR LLMs OR ChatGPT OR Advanced Textual Models) AND (Inventory Management OR Supply Chain Management OR Stock Control).

### 4.1.5 Inclusion Criteria

Given the vast expanse of literature available, it was imperative to set clear boundaries to filter out the most pertinent studies. The following inclusion criteria were established:

- **IC1:** The study must be published in peer-reviewed journals or conferences to ensure credibility.
- **IC2:** The literature should explicitly discuss the application or potential of LLMs or ChatGPT in the realm of inventory management or supply chain management.
- **IC3:** The time frame of publication was considered, ensuring the study is recent enough to capture the latest advancements in the field.
- The typical search phrase employed, based on the above criteria, was: (Large Language Models OR LLMs OR ChatGPT) AND (Inventory Management OR Supply Chain Management) AND "Peer-reviewed".

### 4.1.6 Exclusion Criteria

To ensure the relevance and rigor of the studies included in this research, certain criteria were established to filter out articles that may not directly align with the primary objectives. These criteria were as follows:

- **EC1:** Relevance to the Subject: Any study that did not specifically discuss the integration, application, or potential of Large Language Models (LLMs) within the context of inventory management or supply chain management was excluded. This ensures that the research remains tightly focused on its primary objective.
- **EC2:** Timeliness of the Study: The rapidly evolving nature of artificial intelligence and its applications in supply chain management necessitates the use of the most recent literature. As a result, studies published before 2020 were excluded to ensure the research captures the latest advancements and understandings in the field.
- **EC3:** Comprehensive Analysis: Short papers, typically those less than five pages, were excluded. This criterion was based on the presumption that such papers might not offer a comprehensive analysis or discussion on the topic, which is crucial for a deep understanding of the subject matter.

### 4.1.7 Quality Assessment

Assessing the quality of each selected study is crucial to ensure that the research is built upon reliable and robust foundations. To accomplish this:

1. **Adoption of Kitchenham Guidelines:** Widely recognized in the realm of systematic literature reviews, the Kitchenham guidelines provide a structured approach to

assess the quality of studies. These guidelines offer a set of criteria, each of which is designed to gauge the rigor, relevance, and reliability of a study.

2. **Use of a Predefined Scale:** Each study was assessed based on a predefined scale, typically ranging from "fully meets the criterion" to "does not meet the criterion at all." Some studies might also fall into the "partially meets the criterion" category, reflecting nuances in their approach or content.

3. **Criteria-based Evaluation:** Key criteria for evaluation included the clarity of the study's objectives, the relevance of its methodology, the comprehensiveness of its literature review, the rigor of its analysis, and the relevance of its conclusions. Each study was scored based on how well it met each of these criteria.

The results of this quality assessment were tabulated, offering a clear overview of the strengths and potential weaknesses of each selected study. This comprehensive approach ensures that the research is grounded in high-quality literature, bolstering its validity and reliability. The details of this assessment are showcased in Table 4.2.

### 4.1.8 Conducting the Review

In this pivotal phase, the research process kicked into full gear. Leveraging the groundwork laid in the planning phase, the systematic search was initiated across the identified repositories. The overarching goal was to cast a wide net, capturing a comprehensive set of studies before meticulously refining the selection to zero in on the most relevant pieces. This process was not only about volume but precision, ensuring that the final set of primary studies truly resonated with the research's objectives.

The meticulousness of the review process can't be understated. Each selected study underwent a rigorous assessment, ensuring its alignment with the defined inclusion criteria

Table 4.2: Quality Assessment of Primary Studies

| QAs. | Quality Assessment Criteria |
|---|---|
| QA1 | Are the aims and objectives of the study clearly specified? |
| QA2 | Does the study specifically discuss the integration, application, or potential of Large Language Models (LLMs) within the context of inventory management or supply chain management? |
| QA3 | Does the study offer a comprehensive analysis or discussion on the topic, as evidenced by its methodology, literature review, and conclusions? |

while also verifying its exclusion from any of the exclusion criteria. This dual-edged approach ensured a balance between inclusivity (capturing all relevant research) and exclusivity (omitting tangential or outdated content).

### 4.1.9 Selection of Primary Studies

The journey from a broad collection of studies to a refined list of primary research is a systematic one, and for this study, the tollgate approach served as the guiding light. Rooted in its methodical nature, the tollgate approach is segmented into five distinct phases, each serving as a filter to refine the collection further.

Starting off, all potential duplicates were promptly identified and removed, ensuring the uniqueness of each considered study. From there, each study was assessed through a tiered process. With each tier, or 'tollgate', the criteria became progressively stricter, ensuring that by the end of the fifth phase, only the most relevant, impactful, and aligned studies made the cut.

This iterative process, while time-intensive, ensured the highest level of precision. Each chosen primary study, by virtue of surviving this rigorous selection process, was deemed to offer significant insights that would augment the research's depth and breadth.

## 4.2 Chapter Summary

In this chapter, we delineated the research methodology integral to our study, focusing on the integration of Large Language Models, like ChatGPT, in the realm of inventory management within supply chain systems. To address the formulated research questions, a systematic literature review (SLR) was undertaken, drawing from the latest advancements in the field. The subsequent chapter will introduce and discuss the proposed approach based on insights gathered from this extensive review.

# Chapter Five

# Proposed Framework

## 5.1 Architectural Overview of the Framework

The envisioned framework can be visualized as a series of interconnected layers, each distinctively designed to orchestrate a harmonious interplay of data and insights. Tailored specifically for the multifaceted challenges and opportunities of the supply chain, the framework emphasizes responsiveness and adaptability, especially in the context of inventory management. As illustrated in Fig.1, the framework revolves around four cardinal layers: Data Source, Data Engineering, LLMs, and Applications.

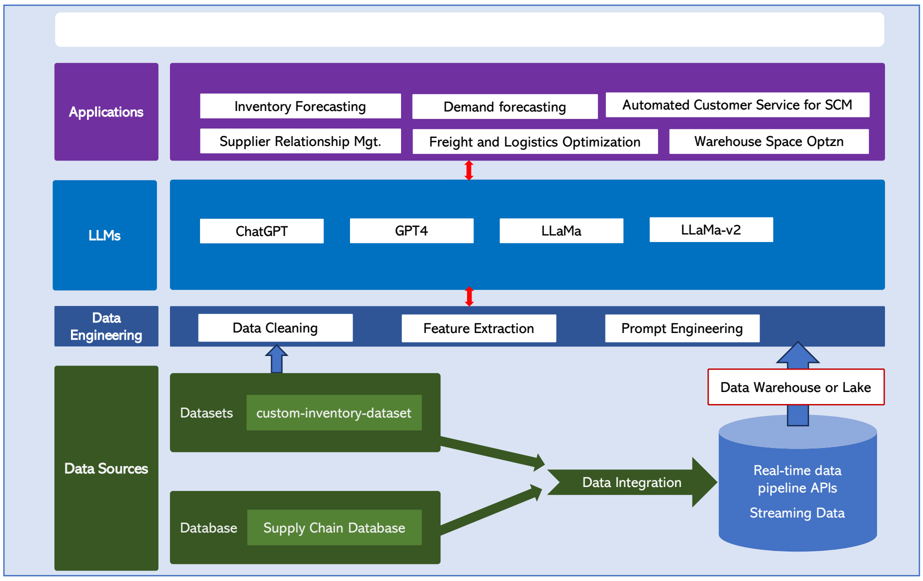


Figure 5.1: Proposed Framework

## 5.2 Framework Layers

### 5.2.1 Data Source Layer

In the ever-evolving landscape of supply chain management, the need for accurate, timely, and comprehensive data is paramount. The foundation of any successful supply chain operation, particularly inventory management, rests on its data sources. This framework has been designed to seamlessly integrate with a multitude of data sources, ensuring a 360-degree view of inventory operations [22]. This foundational layer orchestrates the assimilation of comprehensive inventory management data. It seamlessly integrates with diverse data origins, including:

1. CSV files: A ubiquitous data format that allows for effortless integration.
2. Non-relational databases: These databases offer unmatched scalability, catering to vast and varied data sets.
3. Relational databases: Ensuring that data remains structured and maintains its integrity.
4. Inventory Systems: Platforms like SAP, Oracle, and other inventory management systems are not just data sources but treasure troves of insights. They provide granular details on stock levels, product turnover rates, reorder points, and more. Integrating with these systems allows businesses to stay ahead of demand curves, optimize stock levels, and reduce carrying costs.
5. Warehouse Management Systems (WMS): Warehouses are the beating heart of any supply chain. Systems such as JDA, Manhattan, and HighJump offer a bird's-eye view of warehouse operations. From inventory locations to storage conditions and picking efficiency, these systems provide critical data that can be leveraged to optimize warehouse operations, reduce wastage, and improve delivery times.
6. Database Management Systems (DBMS): In today's digital age, vast amounts of structured data regarding inventory, suppliers, and demand forecasts are stored in DBMSs like MySQL, PostgreSQL, and Oracle DB. This data, when processed and analyzed, can provide insights into supplier performance, inventory turnover, and even predict demand surges or slumps.

7. Data Warehouses & Lakes: With the rise of big data, many organizations are turning to data warehouses and lakes as central repositories for all their data. These systems store everything from sales data to customer feedback, providing a holistic view of operations. Analyzing this data can lead to insights that can revolutionize inventory management strategies, from just-in-time inventory to predictive restocking.

8. Supplier and Manufacturer Portals: The importance of suppliers in supply chain management cannot be overstated. Integrating with supplier and manufacturer portals provides real-time data on lead times, potential supply disruptions, and even insights into raw material availability. This data can be crucial in making informed decisions, ensuring that the supply chain remains uninterrupted.

9. The framework's ability to tap into these varied data sources ensures that businesses have a comprehensive view of their inventory and supply chain operations. Furthermore, the integration capabilities ensure that data is updated in real-time, allowing for real-time decision-making and optimization.

10. By interfacing with these varied data sources, the layer guarantees a rich and holistic dataset, forming the bedrock for subsequent analysis and decision-making processes.

### 5.2.2 Data Engineering layer

The Data Engineering layer stands as a testament to the framework's commitment to harnessing the deluge of data in real-time. In the rapidly evolving realm of supply chain management, this layer is the vanguard, ensuring that data - irrespective of its volume or velocity - is processed with precision and alacrity. A primary focus on real-time Natural Language Processing (NLP) ensures that the data, often unstructured and voluminous, is refined into actionable insights, facilitating informed decision-making.

In the contemporary digital era, the supply chain has transcended its traditional operational paradigms. The advent of real-time order tracking, instantaneous inventory updates, and on-the-fly demand forecasting has redefined the expectations businesses have from their supply chain operations. Delays, once deemed inevitable, are now seen as impediments. Recognizing this seismic shift, the framework's data engineering pipeline has been meticulously architected to operate in synchrony with these real-time demands.

**Data Cleaning: A Prerequisite for Precision** Before data can be leveraged, it must be pristine. The data engineering layer prioritizes this by embarking on a rigorous data cleaning regimen. Whether it's the removal of redundant data, rectification of discrepancies, or the imputation of missing values, the framework ensures that the data is both comprehensive and coherent. Given the relentless pace of supply chain operations, these cleaning operations are executed with unparalleled efficiency, ensuring that decision-making is based on accurate data without any temporal lags.

**Tokenization and Text Processing: Deciphering the Digital Lexicon** The digitization wave, bolstered by the ubiquity of e-commerce, has resulted in a preponderance of textual data within supply chains. Be it intricate product descriptions, candid customer reviews, or crucial supplier correspondences, this text is a reservoir of insights. The framework, equipped with state-of-the-art NLP techniques, ensures this data is not just processed, but understood. Through tokenization, the text is deconstructed into discernible units, which are then processed to extract underlying insights, all in real-time.

**Feature Extraction and Analysis:** From Raw Data to Refined Insights Data, in its raw form, is like unrefined ore; its true value is realized only after processing. The data engineering layer champions this transformation. Through advanced feature extraction techniques, the most salient information is culled from the vast datasets. Whether it's forecasting demand surges, gauging supplier performance, or analyzing inventory dynamics, the framework ensures that businesses have access to the most pertinent insights.

**Continuous Learning and Adaptation:** Staying Ahead in a Dynamic Landscape The only constant in the supply chain sector is change. Challenges emerge, paradigms shift, and new opportunities arise almost daily. The data engineering layer, with its embedded machine learning capabilities, ensures the framework is not just reactive but proactive. Through continuous learning, the system adapts, ensuring businesses remain not just abreast but ahead of these evolving dynamics.

**Monitoring and Alerts:** The Sentinels of Supply Chain Stability In the intricate web of supply chain operations, even minor disruptions can cascade into major setbacks. Recognizing the criticality of uninterrupted operations, the framework incorporates robust monitoring mechanisms. These systems, working tirelessly in the background, identify potential disruptions well before they manifest. Coupled with an efficient alert system, businesses are empowered to preemptively address issues, ensuring the supply chain remains a well-oiled machine.

In essence, the Data Engineering layer is not just a conduit for data processing but the crucible where raw data is refined into actionable insights. Through its myriad functionalities, it ensures that businesses operate with precision, agility, and foresight in the intricate realm of supply chain management [22].

### 5.2.3 Large Language Model Layer

The LLMs layer, strategically positioned at the core of the proposed framework, serves as the linchpin that synergizes various fine-tuning techniques. This central positioning is emblematic of its pivotal role in bridging raw data with actionable insights. With a conscious emphasis on nimble adaptations, this layer ensures the model not only remains aligned with contemporary data landscapes but also stands resilient to the capricious nature of supply chain dynamics.

The essence of this layer lies in its inherent adaptability. In an ecosystem where inventory data is in perpetual flux due to various external and internal factors, maintaining model relevancy is paramount. By perpetually refining the underlying model, the framework is primed to adeptly navigate this fluidity, ensuring its analytical outputs are not just accurate but also resonate with the current zeitgeist of the supply chain environment.

The dawn of the AI era has ushered in a suite of technological marvels, among which Large Language Models (LLMs) like ChatGPT stand out due to their transformative capabilities. These models, with their expansive training data and intricate architectures, have redefined the boundaries of computational linguistics. When channelled towards the nuances of supply chain and inventory management, the potential of LLMs to engender operational metamorphoses becomes palpable [23].

**Integration with LLM APIs:** At the heart of this layer's functionality is its ability to seamlessly meld with established LLMs. Such integrations bestow the framework with unparalleled language processing capabilities, a feature indispensable in the modern, data-driven supply chain landscape. The implications of this are multifaceted [24]. For instance, businesses can leverage this to process a vast array of textual data, from customer feedback elucidating product sentiments to product descriptions that underpin inventory categorizations. Furthermore, the potential to automate customer support, using the nuanced understanding of these models, can drastically enhance user experience while optimizing operational overheads.

**Custom Models and Fine-tuning:** A salient feature of the LLMs layer is its recognition of the heterogeneity inherent in supply chain operations. It acknowledges that while LLMs are robust, there is no one-size-fits-all model. Supply chains, with their unique operational intricacies and challenges, often necessitate bespoke solutions. Catering to this, the framework is architected to be malleable. Businesses are not constrained by generic models; they have the latitude to fine-tune existing architectures or, if required, train bespoke models that are meticulously tailored to their specific operational idiosyncrasies.

In summation, the LLMs layer is not merely a conduit for processing data but is envisioned as a dynamic, adaptable nucleus that ensures the framework's outputs are consistently aligned with the evolving paradigms of supply chain management

### 5.2.4 Application Layer

The crescendo of the framework is undoubtedly represented by the Application layer. Rather than serving merely as a terminal point, this layer illuminates the tangible, real-world utility of the entire framework. It emerges as an exemplar, delineating to potential stakeholders the transformative potential of integrating Large Language Models (LLMs) in reshaping the contours of inventory management and the broader supply chain landscape.

In the contemporary age, where automation and intelligence have become the linchpins of operational efficiency, the integration of LLMs, especially the likes of ChatGPT, heralds a paradigm shift. Their application in the intricate domain of inventory management and supply chain is poised to not only challenge but elevate traditional operational protocols, introducing unparalleled efficiencies and capabilities.

**Inventory Forecasting:** Venturing beyond the conventional methods, LLMs harness historical inventory metrics, sales trajectories, and a myriad of external determinants to astutely project future inventory requisites. This prescient capability is instrumental in mitigating the perennial challenges of stockouts and overstock situations, ensuring businesses maintain optimal inventory equilibrium.

**Supplier Relationship Management:** The dynamics between businesses and their suppliers are intricate. LLMs act as facilitators, enabling real-time, nuanced communication with suppliers. Beyond communication, they adeptly interpret contractual nuances and dissect supplier performance metrics, thereby fortifying the supply chain's foundational relationships.

**Demand Sensing:** LLMs, with their real-time analytical prowess, become the seismographs of the supply chain, sensing even subtle fluctuations in demand patterns. This empowers businesses to recalibrate their inventory strategies proactively, aligning them with market exigencies.

**Warehouse Space Optimization:** The spatial dynamics of warehouses are pivotal for efficiency. LLMs, by scrutinizing product dimensions, sales cadence, and a host of other parameters, proffer recommendations for optimal warehousing strategies, maximizing spatial utilization while bolstering retrieval processes.

**Returns and Reverse Logistics:** The labyrinth of returns is simplified and streamlined by LLMs. By dissecting the reasons for returns, suggesting preventive stratagems, and refining the reverse logistics trajectory, they ensure the returns process is both efficient and insightful.

**Supply Chain Risk Management:** In a globally interconnected supply chain, vulnerabilities are omnipresent. LLMs, by sifting through global news, meteorological data, and a spectrum of external datasets, prognosticate potential disruptions, arming businesses with preemptive mitigation strategies.

**Freight and Logistics Optimization:** The logistics maze is decoded by LLMs as they delve into route analytics, traffic data synthesis, and shipment dynamics to blueprint optimal logistical pathways and modalities.

**Supplier Credit Analysis:** Financial prudence is integral to sustainable partnerships. LLMs, by dissecting financial datasets, predict the creditworthiness of suppliers, ensuring businesses forge alliances with dependable stakeholders.

**Product Lifecycle Management:** Market dynamics and sales trajectories are synthesized by LLMs to inform businesses about product lifecycle strategies, guiding them on product introductions and strategic phase-outs.

**Sustainability Analysis:** In an age where sustainability is paramount, LLMs critically assess a company's supply chain protocols against global sustainability benchmarks, spotlighting areas of enhancement.

**Automated Customer Service for SCM:** Redefining customer interaction paradigms, LLMs, in their avatar as chatbots, address an array of inventory and shipping queries, minimizing human dependencies while amplifying customer satisfaction.

**Supply Chain Education:** As AI-driven pedagogues, LLMs demystify complex supply chain doctrines, offering immersive, on-the-job training modules to professionals.

In synthesizing these multifaceted applications, the framework crystallizes its vision of seamlessly melding AI with inventory management and the broader supply chain. This confluence is not just a harbinger of avant-garde research and innovation but also manifests as pragmatic tools and solutions, enabling businesses to redefine their operational trajectories.

The framework offers a comprehensive solution for integrating AI into inventory management and supply chain. This not only facilitates cutting-edge research and innovation but also offers practical tools for businesses to streamline their operations.

## 5.3 Summary

This chapter elucidates the proposed framework, detailing its layered architecture and the integration of ChatGPT for inventory management in SCM. Each segment of the framework, from data sourcing to application, is meticulously designed to harness the power of AI and LLMs, offering a novel solution for contemporary supply chain challenges. The ensuing chapter will delve into the results and analysis, showcasing the framework's efficacy in real-world scenarios.

# Chapter Six

# Result and Analysis

## 6.1 Chatbot for Inventory Management within Supply Chain Management

### 6.1.1 Experimental Design

The primary objective of this chatbot is to serve as a proof of concept, showcasing the practical integration of Large Language Models, especially ChatGPT, in the domain of inventory management within supply chain management. The chatbot is designed to: Facilitate Real-Time Queries: Users can ask the bot about inventory levels, demand forecasts, supplier details, and other relevant information in real time. Provide Predictive Insights: Leverage the predictive capabilities of LLMs to give insights on inventory needs, potential supply chain disruptions, and supplier performance. Enhance User Engagement: By providing instant, accurate responses, the chatbot aims to improve stakeholder engagement and satisfaction. Optimize Internal Processes: Employees can use the bot for internal queries, thus streamlining operations and reducing manual lookup time.

### 6.1.2 Design Considerations

- User-Friendly Interface: Using Streamlit, the chatbot ensures an intuitive user experience, allowing easy navigation and interaction for users of all technical proficiencies.
- Real-Time Response: The system is designed to provide rapid responses, ensuring that user queries are addressed promptly.
- Scalability: While hosted locally for the proof of concept, the architecture is scalable, allowing potential deployment on larger platforms in the future.
- Context Retention: With prompt construction and chat history management, the bot can maintain context in a conversation, leading to more relevant and coherent interactions.
- Data Integration: The architecture ensures seamless integration with various data sources, ensuring the bot has access to the latest and most relevant data.

### 6.1.3 Technology Stack

- UI: Streamlit Chat provides a lightweight, interactive platform to develop and deploy the chatbot, ensuring an engaging user interface.
- Orchestration: Langchain acts as the middleware, managing the flow of data and ensuring seamless interaction between the user interface and underlying models.
- Prompt Engineering: This layer is crucial for guiding the LLM's responses. It involves Prompt Construction, Chat History, and Context Window Management to ensure the model retains context and provides relevant answers.

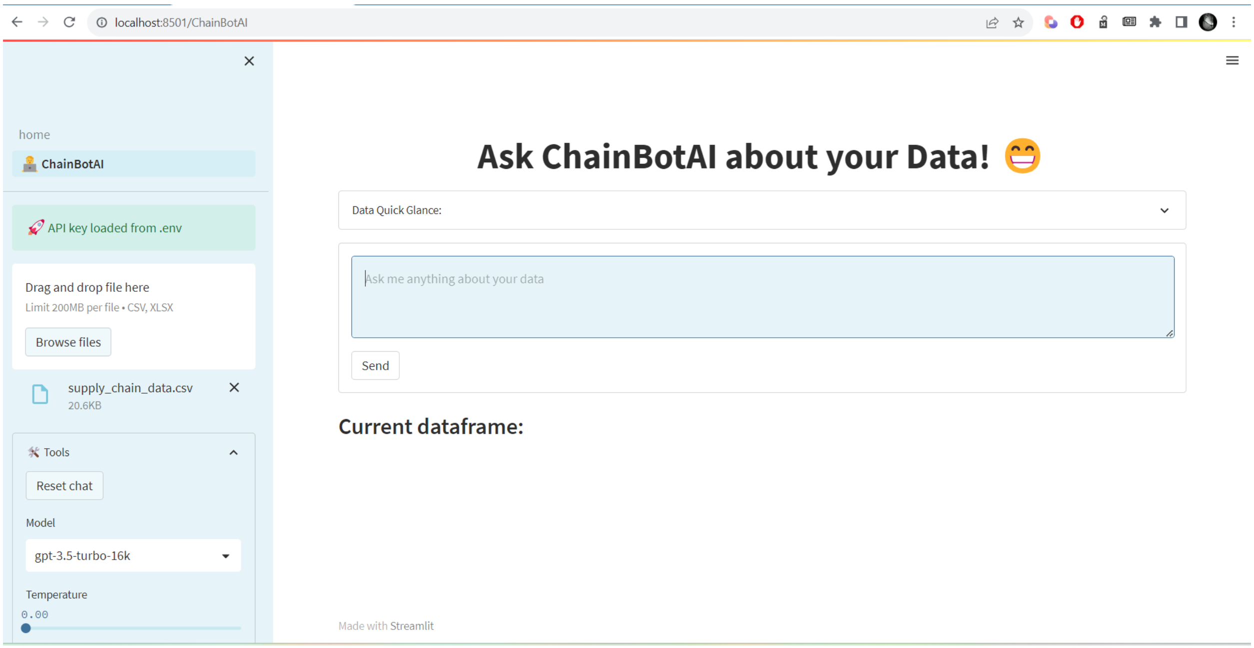


Figure 6.1: ChainBotAI

- Embedding: This layer handles the representation of text data, facilitating faster and more efficient searches. It includes Embedding Model, Vector Database Search, and Data Access Integration.
- Model: ChatGPT 3.5 Turbo is the chosen LLM due to its proven capabilities in understanding and generating human-like text. It's the core that processes prompts and generates responses.
- FAISS: A library for efficient similarity search and clustering of dense vectors.
- CSVLoader: A function from LangChain that helps us load our CSV data.
- ConversationalRetrievalChain: A function from LangChain that helps us create a chatbot that can remember past interactions.
- Runtime: text-davinci is the runtime environment, ensuring that the ChatGPT model runs smoothly and efficiently.

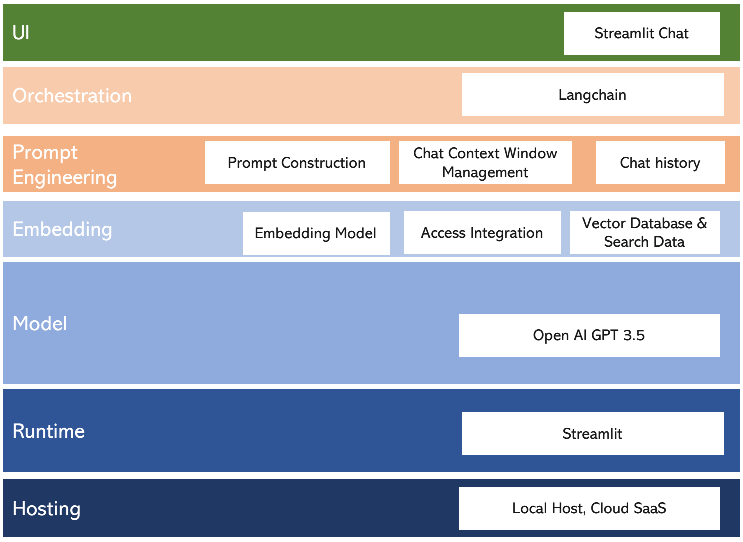


Figure 6.2: ChatBotAI Design Framework

- Hosting: For this proof of concept, the chatbot is hosted locally, allowing for controlled testing and iteration.

The technology stack for our chatbot has been meticulously chosen to ensure optimal performance, scalability, and user experience. Each component of the stack plays a pivotal role in ensuring the chatbot's functionality is robust and efficient.

- Streamlit Chat serves as the foundational user interface for our chatbot. Streamlit, an open-source app framework for Machine Learning and Data Science projects, has emerged as a favorite among developers for its simplicity and interactivity. For our chatbot, Streamlit Chat offers an intuitive platform where users can engage in real-time interactions. This choice was driven by the need for a lightweight, yet powerful interface that can handle the dynamic nature of chat interactions without overwhelming users. The drag-and-drop features, coupled with customizable widgets, ensure that the chat experience remains fluid. Moreover, Streamlit's compatibility with Python ensures that integrating complex algorithms and data-driven insights into the chat is seamless.

- Langchain functions as the orchestration layer. In the world of chatbots, especially those driven by large language models, orchestrating the flow of data and interactions is paramount. Langchain, with its advanced middleware capabilities, acts as the bridge between the user's input and the underlying models. It manages the data flow, ensuring that user queries are parsed correctly, directed to the appropriate models, and that the returned responses are structured suitably for user consumption. The decision to incorporate Langchain was influenced by its proven efficiency in managing interactions in real-time applications and its compatibility with various language models.
- The Prompt Engineering layer is at the heart of our chatbot's intelligence. While Large Language Models like ChatGPT are inherently capable of understanding and generating human-like responses, guiding these models to generate specific, relevant, and context-aware responses is crucial. This is where the intricacies of Prompt Construction come into play. By crafting specific prompts, we can guide the model's responses to fit the exact needs of the user. Additionally, retaining chat history and managing the context window ensures that the chatbot understands the flow of the conversation, allowing for coherent and contextually relevant interactions. This layer essentially fine-tunes the chatbot's capabilities, ensuring that while the vast knowledge of the LLM is leveraged, the responses remain tailored to the specific context of inventory management within supply chain management.
- Embedding is a pivotal component in ensuring the efficiency of our chatbot. With

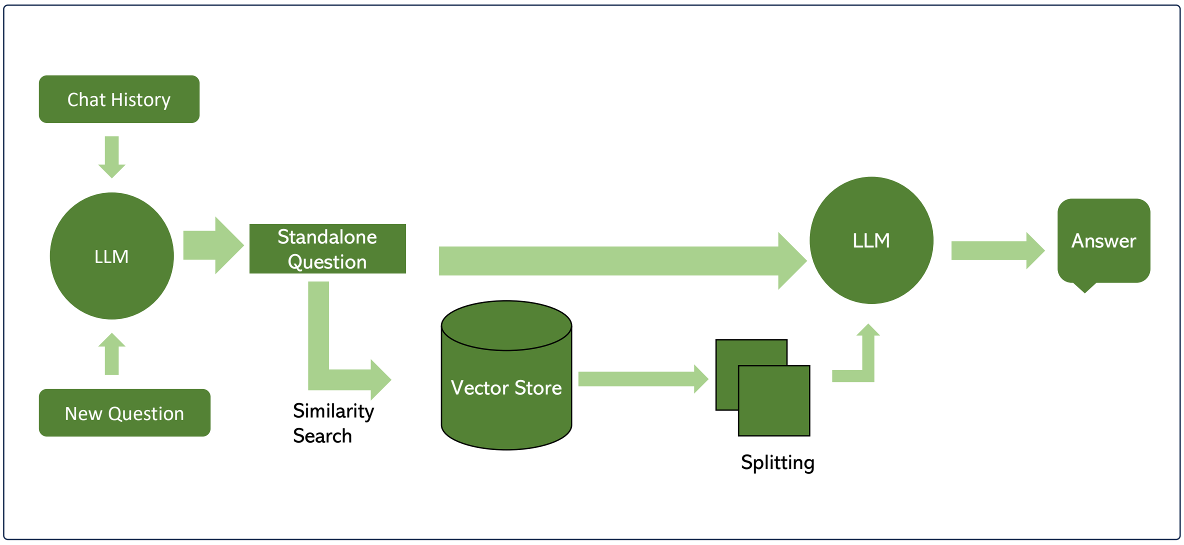


Figure 6.3: ChainBotAI Process

the massive amount of data that needs to be processed in real-time, representing this data in a manner that is computationally efficient is crucial. The embedding model transforms raw text data into numerical vectors, which can then be quickly compared for similarities. This enables our chatbot to rapidly search its database for relevant information or similar past queries. Coupled with the Vector Database Search, this layer ensures that data retrieval is lightning-fast. Furthermore, the Data Access Integration feature ensures that the chatbot can seamlessly connect with various data sources, be it local databases, data lakes, or external APIs, ensuring that the chatbot always has access to the most up-to-date and relevant information.

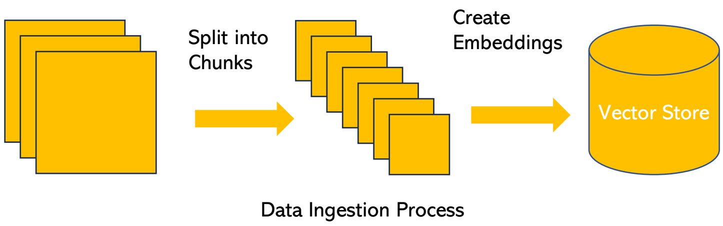


Figure 6.4: Data Ingestion Process

At the core of our chatbot's intelligence is the ChatGPT 3.5 Turbo model. ChatGPT, developed by OpenAI, stands at the forefront of Large Language Models. With its vast training data and sophisticated architecture, ChatGPT can understand and generate text that is virtually indistinguishable from human-written content. For our purposes, this model provides the chatbot with the ability to understand complex queries related to inventory management, process the underlying data, and generate insightful and accurate responses. The choice of the Turbo variant ensures that the chatbot remains efficient even under heavy loads, making it suitable for real-world applications where numerous users might be interacting with the bot simultaneously.

To ensure that the ChatGPT model operates seamlessly, the text-davinci runtime environment is employed. This runtime ensures that the model's computations are efficient, and any potential issues or bugs are swiftly dealt with. It provides a stable platform where the LLM can operate at its full potential without being bogged down by technical glitches.

Lastly, for the proof of concept, the entire chatbot system is hosted locally. Local hosting offers several advantages at this stage. It allows for rapid testing and iteration, ensuring that any changes or improvements can be implemented and tested in real-time. Furthermore, local hosting provides a controlled environment, free from potential external disruptions, ensuring that the initial testing and demonstrations of the chatbot are smooth.

The technology stack for our chatbot has been chosen to ensure a seamless blend of user experience, computational efficiency, and intelligent, context-aware interactions. Each component, from the user interface to the underlying model, plays a crucial role in ensuring the chatbot's success in the domain of inventory management within supply chain management.

## 6.2 Testing And Validation

Our framework's deployment is meticulously designed to cater to the modern needs of inventory management. At its core, it features a front-end service tailored for multi-user interaction, ensuring that various stakeholders can seamlessly engage with the system. This is complemented by our Langchin connection, which bridges our system directly to OpenAI, granting us the power of Large Language Models (LLMs). To ensure continuous availability and efficient data management, we've integrated Streamlit for local deployment. It updates data in a round-robin manner, guaranteeing that there's always a set of Virtual Machines (VMs) ready to support user interactions. For the LLMs, we've chosen GPT-gpt-3.5-turbo-16k and gpt-3.5-turbo, given their proven capabilities.

The initial reactions from our users have been overwhelmingly positive. They've highlighted the framework's potential in helping them grasp the intricate optimization logic behind their inventory data. A standout feature, as noted by many, is the ability to format queries in a way that ensures the bot's responses are grounded in the provided dataset, minimizing data hallucination. This was particularly evident when the prompt was explicitly instructed to answer questions based solely on the given data, as illustrated in the code segment below.

**Performance Setup and Observations**: For our performance evaluation, we adopted a structured approach. For each scenario, we conducted 10 experiments. In every experiment, we assessed at least 10 question sets. Typically, a question set comprises between 10 to 30 questions and their corresponding answers. Both GPT-gpt-3.5-turbo-16k and gpt-3.5-turbo were employed for this evaluation. Our findings, which span different LLMs, example selection methods, and example set sizes, are consolidated in Table 1. A consistent observation across the board was the LLMs' stable performance.

To provide a clearer picture, here are some of the questions posed during the evaluation. It was evident that the LLMs excelled, especially with questions involving straightforward mathematical calculations:

Q1: Given the historical sales and market trends data, what is the projected demand for the next quarter?

Q2: What are the current stock levels, and how do they compare to the optimal levels recommended based on lead time, demand variability, and service level targets?

Q3: How many products were returned last month, and what were the primary reasons cited by customers for those returns?

Q4: Considering the past six months, how often has the lead time varied from the expected duration, and by what average margin?

Q5: Based on the current inventory and associated costs, what is the total valuation of the stock on hand?

These questions are framed to align with the challenges and potential insights an LLM could provide in the realm of inventory management.

It's essential to note that there isn't a universally accepted method for evaluating chatbots as of now, underscoring the pioneering nature of this work.

## 6.3 Discussion

The integration of Large Language Models (LLMs) into inventory management systems represents a significant leap in the evolution of supply chain optimization. Our framework, as described, is a testament to this advancement, meticulously designed to address the

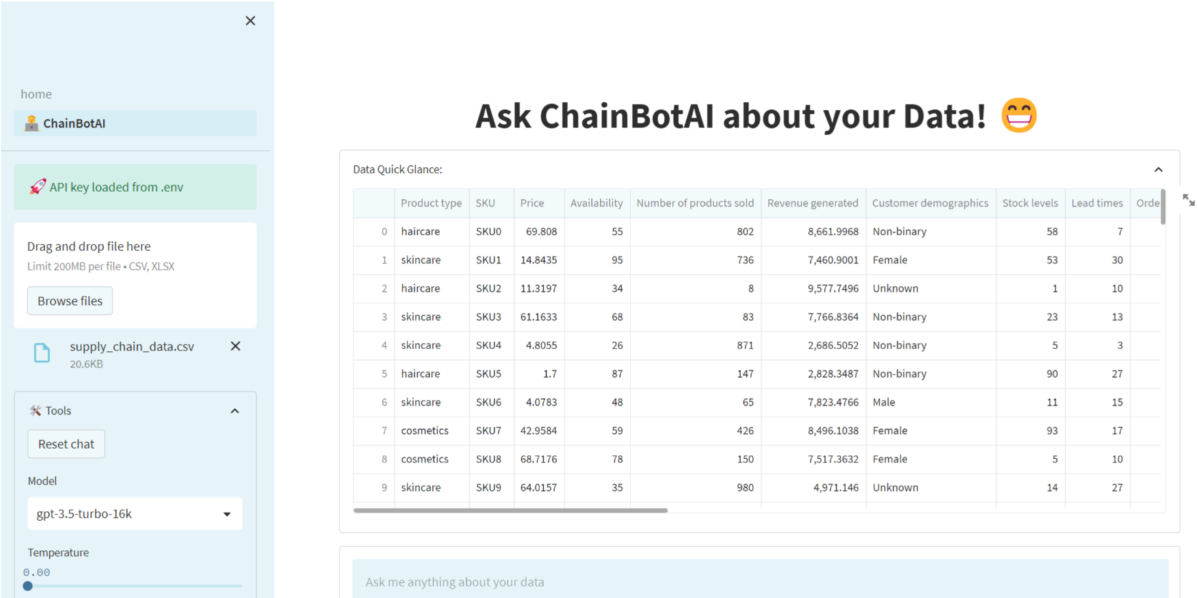


Figure 6.5: Data Ingestion

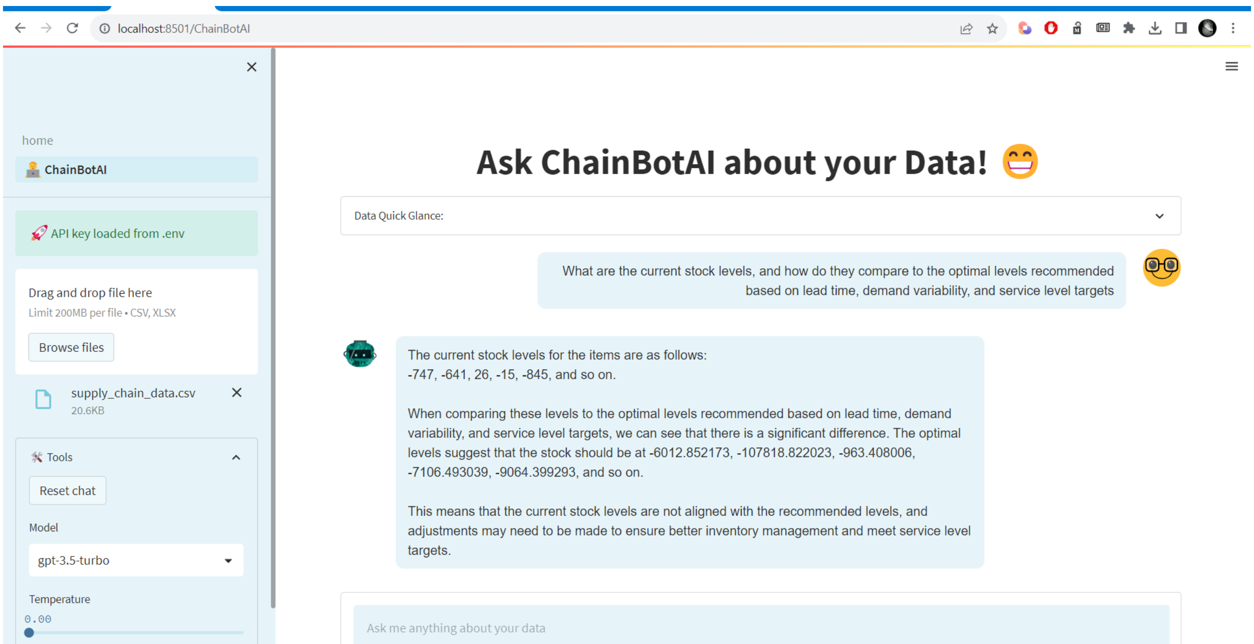


Figure 6.6: ChatBotAI Response

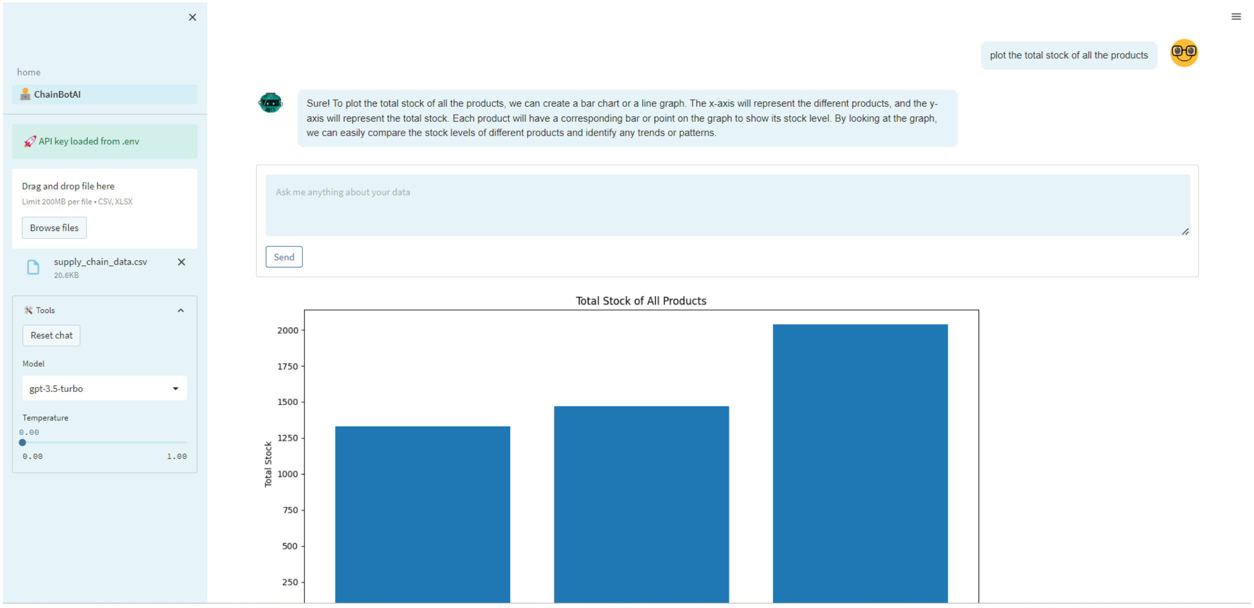


Figure 6.7: ChainBotAI Analytics

multifaceted challenges of contemporary inventory management.

Central to this design is the emphasis on user interaction. The front-end service, tailored for multi-user engagement, ensures that the system is not just a tool but an interactive platform. This is further enhanced by the Langchin connection, which serves as a conduit to OpenAI, bringing the capabilities of LLMs to the forefront of inventory management.

Streamlit's integration is a strategic decision, reflecting the importance of continuous availability in real-time inventory management. The round-robin data updating mechanism ensures that there's no downtime, a critical feature in the dynamic world of supply chain where delays can have cascading effects.

The choice of LLMs, specifically GPT-gpt-3.5-turbo-16k and gpt-3.5-turbo, was not arbitrary. Their selection was based on their demonstrated efficacy in handling complex linguistic tasks, a necessity when dealing with intricate inventory queries.

User feedback is the litmus test for any system. The overwhelmingly positive initial reactions underscore the framework's potential. The ability to ground the bot's responses in the provided dataset, ensuring minimized data hallucination, stands out as a significant achievement. This feature, as evidenced by user interactions, is pivotal in ensuring that the system's outputs are not just accurate but also contextually relevant.

Our performance evaluation methodology was rigorous, ensuring that the LLMs were tested across a spectrum of scenarios. The consistent performance of the LLMs, irrespective of the variations in example sets and selection methods, is indicative of their robustness.

The questions posed during the evaluation were not generic but tailored to reflect real-world inventory management challenges. From projecting demand based on historical data to assessing stock valuations, these questions encapsulate the breadth and depth of inventory management.

However, it's crucial to contextualize these advancements within the broader landscape of chatbot evaluation. The absence of a standardized evaluation method for chatbots highlights the nascent stage of this technology, even as it underscores the pioneering nature of our work.

In conclusion, while our framework represents a significant stride in inventory management, it's essential to view it as a dynamic tool, one that will evolve in tandem with advancements in LLMs and the ever-changing demands of supply chain management.

# Chapter Seven

# Conclusion and Future Work

## 7.1 Conclusion

As the digital revolution advances, the integration of Large Language Models (LLMs), specifically ChatGPT, into various sectors has become a pivotal point of exploration. This dissertation embarked on an investigative journey into the application of ChatGPT within the realm of Inventory Management as part of Supply Chain Management.

Our initial investigation, grounded in a comprehensive literature review and preliminary studies, painted a picture of the transformative potential that LLMs hold. They have the capability not just to optimize but to revolutionize the processes and functions within supply chain operations. As highlighted in our results, applications such as route optimization, predictive maintenance, and data analysis stand as testament to the strategic advantages of ChatGPT in reducing costs and enhancing process performance.

However, with innovation comes challenges. The dependency on precise queries, the necessity for application-specific components, and the potential for undetected mistakes are just a few of the hurdles to be addressed. These challenges are not insurmountable, but they emphasize the importance of human expertise in tandem with technological solutions. As observed in the study, while ChatGPT can provide robust support, it cannot replace the nuanced expertise of supply chain professionals.

The transformative integration of LLMs like ChatGPT into sectors like finance, as alluded to in the provided texts, further underscores the vast opportunities and complexities that lie ahead. As with all emergent technologies, it's crucial to navigate these complexities with a balanced view, understanding both the immense potential and the inherent challenges.

The proposed framework in this dissertation serves as a blueprint for organizations looking to integrate ChatGPT into their inventory management systems. This structured approach, from data sourcing to application, offers a systematic way to harness the power of LLMs while mitigating potential pitfalls.

In conclusion, the future of Inventory Management within Supply Chain Management is poised at the cusp of a transformative era. The integration of Large Language Models, particularly ChatGPT, offers a promising avenue to elevate operational efficiency, decision-making, and strategic planning. Yet, it is imperative to approach this integration with a discerning eye, recognizing that while technology can significantly augment processes, the human element remains indispensable.

The symbiotic relationship between ChatGPT and supply chain professionals will be the cornerstone of future advancements, ensuring that while we leverage the prowess of artificial intelligence, we also uphold the values, ethics, and expertise that only humans can bring to the table. As organizations venture into this new frontier, it is our hope that this dissertation serves as a guiding light, illuminating both the opportunities and challenges that lie ahead.

## 7.2 Future Work

The exploration into the integration of ChatGPT in Inventory Management has opened up a plethora of avenues for further research. A deeper dive into specific applications, such as route optimization or predictive maintenance, could provide more granular insights and pave the way for specialized solutions.

Addressing the challenges identified in this dissertation is paramount. Future studies could focus on refining the interaction mechanisms with ChatGPT to reduce the dependency on precise queries. Additionally, research into developing safeguards against undetected mistakes and enhancing the model's understanding of context could lead to more reliable and robust applications.

The proposed framework in this dissertation offers a structured approach to integrating ChatGPT into inventory management systems. However, its real-world applicability and scalability remain to be tested on a wide scale. Pilot studies in real-world supply chain environments would provide invaluable feedback and insights into its strengths and areas for improvement.

Furthermore, as ChatGPT and similar LLMs continue to evolve, it would be beneficial to revisit and update the integration strategies periodically. This ensures that organizations can leverage the latest advancements in the field.

Lastly, while this dissertation focused on Inventory Management within Supply Chain Management, the principles and findings could potentially be applied to other sectors. Exploring the applicability of ChatGPT in areas like procurement, logistics, or even outside the supply chain domain, such as customer service or finance, could be a fruitful direction for future research.

# Appendix One

# Project Code

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