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Project Proposal

Supply Chain and Logistics Management Demand Forecasting Using Explainable AI

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ABSTRACT

Problem: Since it allows for well-informed decisions to be made regarding production, inventory control, and procurement, accurate demand forecasting is essential to supply chain and logistics management. Even if they are very accurate, contemporary forecasting methods like ensemble learning, XGBoost, and Long Short-Term Memory (LSTM) operate as "black box" models that are difficult to understand. Supply chain planners, who have to defend model-driven recommendations to management, lose credibility as a result of this opacity.

Methodology: To close the gap between interpretability and accuracy, this study suggests a hybrid forecasting framework that incorporates Explainable Artificial Intelligence (XAI) methodologies. To highlight significant temporal patterns, the study uses SHAP (SHapley Additive exPlanations) to identify feature contributions and attention visualization within LSTM models. The M5 Forecasting - Walmart Sales Dataset and the UCI Supply Chain Dataset will be used for the experiments.

Initial Results: According to early tests, incorporating SHAP-based feature analysis enhances interpretability without sacrificing precision. Competitive accuracy was attained by the LSTM-XGBoost ensemble on validation subsets of the M5 dataset. Promotions, price adjustments, and seasonal effects were all correctly recognized by SHAP visualizations as major demand drivers, offering useful information for decision-making.

Subject Descriptors (ACM):

- Information systems → Decision support systems → Data analytics for supply chain management

- Computing methodologies → Machine learning → Time series forecasting

Keywords: Explainable AI, Demand Forecasting, Supply Chain Management, SHAP, Counterfactual Analysis

Table of Contents

Table of Figures

Chapter 01: Introduction

1.1 Chapter Overview

By examining the importance of demand forecasting in supply chain and logistics management, the difficulties presented by black-box prediction models, and the need for explainable artificial intelligence (XAI) methodologies, this chapter provides an overview of the research's foundation. After providing the problem's background and context, it goes on to provide a thorough problem definition and statement that lists the issues this study aims to address. The chapter then goes over the reasons for conducting this research and examines previous studies in this area, pointing out the main gaps that remain. These restrictions result in the discovery of research gaps that support the necessity of this undertaking.

Overall, this chapter provides a clear grasp of the research setting, the limitations of existing methods, and the strategy this study will follow to address the issues that have been found.

1.2 Problem Background

One of the most important aspects of supply chain and logistics management is demand forecasting. It has a direct impact on important business processes like transportation planning, production scheduling, inventory control, and procurement. Organizations may reduce holding costs, increase customer satisfaction, and effectively manage supply and demand with accurate projections. However, the dynamic and unpredictable nature of global marketplaces, seasonal variations, promotions, and disruptions like pandemics or geopolitical events have made demand forecasting more difficult in today's data-rich environment.

Forecasting accuracy has increased dramatically in recent years thanks to machine learning (ML) and deep learning (DL) models.

Traditional statistical methods like exponential smoothing or ARIMA are outperformed by models like ensemble methods, Gradient Boosted Trees (XGBoost), and Long Short-Term Memory (LSTM). Even still, even very effective models function as "black boxes," providing little to no explanation for the reasoning behind or methods by which particular predictions are generated. Since planners must defend and clarify forecasts to management teams and operational decision-makers in real-world supply chain settings, this lack of interpretability has grown to be a significant adoption obstacle.

1.3 Problem Definition

A conundrum has been generated by the increasing intricacy of global supply chains and the growing dependence on AI-driven forecasting: while contemporary machine learning models provide remarkable prediction accuracy, they are frequently viewed as unreliable due to the opaque nature of their internal operations. Managers and planners find it difficult to determine the precise causes of a prediction change or why it has changed. Adopting such models for crucial decision-making is therefore extremely difficult for companies.

The goal of this study is to address the issue of demand forecasting models used in supply chain and logistics management having poor interpretability and few practical explanations. Although the majority of current models generate forecasts as numerical outputs, they hardly ever offer insights or suggestions that are easy for humans to understand. The proposed project will concentrate on incorporating Explainable AI (XAI) methods into demand forecasting frameworks, including attention visualization, counterfactual reasoning, and SHAP analysis. In order to improve decision-making, stakeholders will be able to simulate "what-if" scenarios and comprehend the primary drivers of forecasts. The ultimate goal of the project is to convert opaque forecasting systems into transparent, decision-supporting instruments that improve supply chain experts' usability and trust.

1.3.1 Problem Statement

The interpretability and practical explanations of contemporary demand forecasting models in supply chain management are lacking, which restricts their credibility and decision-makers' ability to use them.

1.4 Research Motivation

The practical difficulties of interpreting AI-based forecasts and the growing reliance of global supply chains on data-driven decision-making serve as the driving forces behind this study. While working with real-world forecasting systems, many organizations face situations where highly accurate models are rejected because users cannot explain or justify their outputs. This example emphasizes the necessity of predicting models that are visible, interpretable, and accurate. This study intends to enable planners and managers to comprehend model reasoning, develop confidence in AI-driven recommendations, and make better operational decisions by integrating Explainable AI techniques into demand forecasting. The task is technically difficult since it calls for combining time-series forecasting systems with interpretability frameworks (such as SHAP and counterfactuals) while preserving prediction accuracy.

1.5 Existing Work

Citation	Summary	Limitation	Contribution
Jahin M.A., Shahriar, A., & Al Amin, M. (2024).	Proposed an explainable hybrid CNN-LSTM-GRU model for demand forecasting usi source data.	Focused only on feature importance; lacks actionable insights.	Improved accuracy with partial explainability.
Zhu, R., Christensen, C., Zarrin, B., & Alstrøm, T. (2025).	Defined a user-centric explainability framework for supply chain demand planning.	Conceptual; no practical model implementation.	Framed explainability needs in SCM context.
Arboleda-Florez, M., & Castro-Zuluaga, C. (2023).	Applied SHAP to explain ML-based forecasts in direct sales.	Lacked counterfactual or simulation explanations.	Showed feasibility of using SHAP for demand forecasts.
Nair, A., & Subramanian, K. (2022).	Reviewed AI techniques for SCM forecasting and their effectiveness.	Most works emphasize accuracy, not interpretability.	Highlighted need for explainable forecasting models.

Citation	Summary	Limitation	Contribution
Zhou, Y., & Wang, L. (2023).	Developed an LSTM model enhanced with XAI for purchase prediction.	Lacks decision-support or what-if analysis.	Demonstrated XAI’s potential for transparent predictions.

1.6 Research Gap

Even with significant advancements in AI-driven demand forecasting, supply chain decision-makers are still unable to understand and use these systems effectively due to existing research and industrial implementations. The majority of current research places a strong emphasis on model accuracy while ignoring the necessity of practical decision support and reasoning that is understandable to humans. In particular:

- Counterfactual or what-if explanations are rarely incorporated into forecasting systems to inform operational choices.
- The explainability techniques used today (such as SHAP and feature importance) only highlight the factors that have an impact; they do not demonstrate how changing those factors influences results.
- Attention-based visualization is not widely used to highlight significant time periods or event drivers.
- In empirical forecasting contexts, user-centric trust and interpretability evaluation are still not well studied.

Thus, the lack of an interpretable, decision-oriented forecasting framework that blends interpretability, transparency, and actionable knowledge is the research gap that this study attempts to fill. This project aims to convert "black-box" prediction systems into transparent tools that allow planners to comprehend, trust, and act upon AI-driven supply chain management suggestions by incorporating Explainable AI into demand forecasting.

1.7 Contribution to Body of Knowledge

By offering an explainable AI-based method for supply chain demand forecasting that closes the gap between prediction accuracy and interpretability, this study advances both the problem and research domains. Through human-interpretable explanations, it offers a workable solution in the problem domain that helps supply chain planners comprehend and have faith in AI-driven forecasts.

By incorporating Explainable AI (SHAP, counterfactual reasoning, and attention visualization) into forecasting models, it expands on current knowledge in the research domain and offers clear, actionable insights for logistics and inventory management decision-making.

1.7. 1 Contribution to Problem Domain

Forecasting in the modern supply chain depends on intricate models that frequently function as "black boxes." Managers find it difficult to understand AI-generated outcomes and relate them to operational decisions like pricing changes or procurement plans.

This research presents an Explainable Demand Forecasting Framework that simulates alternative scenarios ("If price is reduced by 10%, demand increases by 15%") and using counterfactual reasoning to uncover influential features (such as promotions, seasonality, and external events) using SHAP analysis.

Important contributions consist of:

- Human-Understandable Forecasts: To increase decision confidence, include both written and visual explanations for each prediction.
- Actionable Insights: Creating hypothetical scenarios to link forecasts to choices like logistics planning or order quantity.
- Trust and Transparency: Enabling planners to use comprehensible evidence to support projections to management.
- Operational Value: Improving responsiveness to outside changes, decreasing stockouts, and lowering uncertainty in demand planning.

1.7.2 Contribution to Research Domain

This study adds to the developing field of Explainable AI in time-series forecasting within the research domain. Few studies have combined several XAI approaches into a useful forecasting framework, whereas earlier research has examined SHAP or attention mechanisms separately.

This study offers:

- Integrated XAI-Driven Forecasting Framework: combining LSTM and XGBoost models with interpretability tools (SHAP, counterfactuals, and attention visualization).
- Methodological Advancement: Showing how XAI may improve transparency without sacrificing the precision of the model.

- Beyond feature attribution, decision-oriented explainability refers to reasoning that is scenario-based and actionable.
- Impact of the Research: Developing a repeatable process for integrating XAI into supply chain management operational forecasting duties.

1.8 Research Challenges

1.8.1 Challenge of Real-Time Risk Detection in High-Traffic Environments

Challenge: One of the main technological challenges is maintaining the model's interpretability while achieving high forecasting accuracy. Although ensemble techniques like XGBoost and deep learning models like LSTM frequently produce better accuracy, they function as "black boxes," making it challenging for planners to comprehend how inputs impact results.

Justification: Planners may become less confident in the model's suggestions if its internal logic is not readily apparent. The difficulty is in incorporating Explainable AI procedures that give decision-makers transparency and meaning while preserving the accuracy benefits of sophisticated AI models.

1.8.2 Adaptive Rate Limiting

Problem: The majority of explainability techniques, like SHAP or feature importance ranking, outline the factors that affect demand but don't explain how these findings can be used to take useful action.

Justification: When making operational decisions like amending lead times, altering order amounts, or adjusting prices, planners need justifications. Overcoming descriptive explanations and offering practical, decision-based insights that immediately assist supply chain operations is the difficult part.

1.8.3 Challenge of Data Collection and Model Training

The integration of several information, including past sales, promotions, seasonality, and external factors like weather or economic indicators, is necessary for accurate demand forecasting. These data sources frequently have inconsistent data, missing values, and different time

Rationale: Incomplete or low-quality data can cause the model to be misguided and impair its interpretability and accuracy. Constructing reliable preprocessing and data-fusion pipelines that guarantee consistency, completeness, and dependability across all input variables is the difficult part.

1.8.4 Challenge of Integration with Microservice Ecosystem

Challenge: Because of changes in consumer behavior, market trends, or disruptions, demand patterns in supply chains fluctuate regularly. It is difficult to guarantee that the explainable forecasting model will continue to be reliable and flexible under such circumstances.

Justification: When confronted with unfamiliar situations or unanticipated events, a model built on static data may not perform as expected, eroding confidence in its predictions. Designing an adaptive system that continuously learns and recalibrates while maintaining the outputs' interpretability and transparency is a problem.

1.9 Research Questions

RQ1: How can demand forecasting models incorporate Explainable AI to improve interpretability without sacrificing accuracy?

RQ2: Which explainability strategies work best for supply chain decision-making, such as SHAP, counterfactuals, and attention visualization?

RQ3: How can managers and planners use forecast explanations to gain practical insights?

RQ4: How can the suggested model remain dependable and flexible in the face of shifting demand trends and outside interruptions?

1.10 Research Aim

The purpose of this study is to create, develop, and assess a demand forecasting framework based on Explainable AI that improves supply chain management decision-making efficiency, transparency, and trust. In order to help planners comprehend, defend, and act upon forecasts, the system will incorporate counterfactual reasoning, attention visualization, and SHAP-based feature interpretation into LSTM and XGBoost forecasting models.
Through the transformation of intricate AI predictions into insightful, human-understandable information, the suggested methodology aims to close the gap between model accuracy and interpretability.

The ultimate goal of this project is to enable supply chain experts to make proactive, transparent, and data-driven decisions that enhance overall operational efficiency and forecasting dependability.

1.10 Research Objectives

Objectives	Description	LOs Mapped	RQ Mapped
Problem Identification	Determine the interpretability and decision support shortcomings of the	LO1, LO4	RQ1

	demand forecasting models in use today.		
Literature Review	Examine in-depth the AI and XAI techniques applied to SCM demand forecasting.	LO1, LO4	RQ1, RQ2
Requirement Elicitation	Using domain analysis and literature, identify the functional and non-functional needs for an explainable forecasting system.	LO3, LO6	RQ2
System Design	Create a transparent hybrid forecasting framework by combining LSTM, XGBoost, and XAI techniques.	LO1, LO3, LO6	RQ1, RQ2
Implementation	Create and train forecasting models utilizing SHAP and counterfactual techniques on actual or benchmark supply chain datasets.	LO2, LO5, LO7	RQ1, RQ3
Testing	Conduct experiments to assess forecasting accuracy (RMSE, MAPE) and explanation quality (usefulness, clarity).	LO1, LO7, LO8	RQ3, RQ4

Documentation	Create a well-organized research report that includes technical, professional, and ethical views on the findings.	LO2, LO6, LO9	RQ4

1.11 Project Scope

1.11.1 In Scope

- In supply chain and logistics, pay close attention to short- and medium-term demand forecasting.
- use of Explainable AI techniques (attention visualization, counterfactuals, and SHAP).
- assessment using specific datasets and metrics for interpretability and accuracy.

1.11.2 Out Scope

- deployment in real time in operational business settings.
- including unforeseen outside disturbances like political upheavals or natural disasters.
- decision systems based on reinforcement learning and multi-agent optimization.

1.12 Hardware/Software Requirements

Hardware Requirements	Specification
Processor	Intel Core i7 / AMD Ryzen 7 or higher
RAM	16 GB minimum
GPU	NVIDIA RTX 3060 or equivalent (6 GB VRAM)
Storage	512 GB SSD minimum
Operating System	Windows 11 / Ubuntu 22.04
	Python 3.10

Programming Language	
Frameworks/Libraries	TensorFlow, Scikit-learn, XGBoost, SHAP, Matplotlib
Tools	Jupyter Notebook, Visual Studio Code, Google Docs
Database	CSV/SQL data sources for demand datasets

1.13 Chapter Summary

The study topic, Explainable AI for Supply Chain Demand Forecasting, was introduced in this chapter by outlining the problem's description, motivation, background, and gaps in the body of literature. It described how decision-making and trust are hampered by black-box forecasting algorithms and provided evidence for integrating Explainable AI to close this gap. The research aim, objectives, scope, and obstacles that direct this study were also specified in this chapter.

The suggested approach aims to enable supply chain experts to make transparent, data-driven decisions based on intelligible AI insights by fusing interpretability, accuracy, and actionability.

Chapter 02: Literature Review

2.1 Chapter Overview

In order to improve interpretability and decision-making, this chapter offers a thorough analysis of the body of research on demand forecasting in supply chain and logistics management, with an emphasis on the application of Explainable Artificial Intelligence (XAI). The issue domain is first described, with a focus on the significance of precise and open forecasting for operational effectiveness in manufacturing, inventory management, and procurement. The main methods and approaches utilized in demand forecasting are then examined in this chapter, including deep learning, machine learning, and statistical models. Their structures, benefits, and intrinsic drawbacks are covered, with special attention paid to high-performing predictive systems' difficulty to be explained.

The next sections examine the development of Explainable AI in forecasting, examining the ways in which interpretability techniques like SHAP, LIME, and counterfactual reasoning have been used to boost user confidence and model transparency. Decision-oriented explainability frameworks that connect forecast results to useful business insights are also taken into account in the evaluation.

A critical assessment of previous research is presented at the end of the chapter, emphasizing its advantages, disadvantages, and research gaps that support the creation of the suggested Explainable AI-based Demand Forecasting Framework for supply chain management.

2.2 Problem Domain

Demand forecasting is essential to operational effectiveness, cost reduction, and customer satisfaction in contemporary supply chain and logistics management. Organizations may reduce waste, stockouts, and excess inventory by matching production, inventory, and procurement strategies with projected market demand thanks to accurate forecasts. However, because of shifting consumer behavior, unstable market conditions, and outside disturbances like world crises and economic upheavals, predicting has grown more difficult.

Based on past data, traditional forecasting techniques including regression models, exponential smoothing, and ARIMA have long been used to estimate future demand. Although these techniques offer a basis for short-term forecasting, they frequently find it difficult to adjust to nonlinear trends and abrupt changes in the market. Researchers have used machine learning (ML) and deep learning (DL) models, like Random Forest, XGBoost, and LSTM networks, which can capture intricate temporal dependencies and nonlinear interactions, to get around these restrictions. Although accuracy has greatly increased thanks to these models, a new problem has emerged: interpretability issues.

High-performing but opaque "black-box" models are widely used, which is the key challenge in the problem domain. The inability of supply chain managers and planners to comprehend why a model forecasts a particular demand value undermines confidence and restricts adoption in commercial contexts. It becomes difficult to defend strategic choices like raising order quantities, changing prices, or modifying logistical plans in the absence of clear justification. Recent research (Jahin et al., 2024; Zhu et al., 2025; Arboleda-Florez & Castro-Zuluaga, 2023) have brought attention to this discrepancy between explainability and predictive performance, highlighting the necessity of forecasting systems that are interpretable and decision-supportive.

Furthermore, most current models produce numerical results without converting them into useful information. In addition to "what will happen," planners need to know "why it will happen" and "what can be done to change it." Promising solutions to bridge this gap include explainable AI techniques like attention visualization for time-based analysis, counterfactual reasoning for scenario simulation, and SHAP for feature importance. By incorporating these methods into forecasting, AI-driven insights can become more interactive, comprehensible, and applicable to operations.

Thus, creating an Explainable AI-driven demand forecasting framework that promotes actionable decision-making, increases model transparency, and boosts confidence among supply chain experts is the issue area this study addresses. This cohesive strategy aims to close the gap between technical forecasting performance and practical business usefulness by striking a balance between interpretability and predictive accuracy.

2.3 Existing Work

It is widely accepted that precise demand forecasting is essential to supply chain and logistics management optimization, which motivates large investments in cutting-edge AI and machine learning models. When it comes to identifying intricate, non-linear patterns in historical data, techniques like Long Short-Term Memory (LSTM) networks, XGBoost, and complex ensembles have proven to be more effective than conventional statistical methods (Nair & Subramanian, 2022). However, the "black-box" nature of these high-performing models often prevents their widespread adoption in real-world supply chain planning. There is a big disconnect between the promise of models and their practical implementation since planners and managers are frequently reluctant to believe and follow forecasts whose logic is opaque (Zhu et al., 2025). In order to overcome this lack of confidence and convert unrefined forecasts into useful business intelligence, this has spurred an increasing amount of research on Explainable AI (XAI).

Using post-hoc explanation strategies to demystify complex model predictions has been the main focus of previous work. The application of SHAP (SHapley Additive exPlanations) to measure the contribution of each input characteristic to a particular forecast is a well-known example. In a direct sales setting, for example, Arboleda-Florez and Castro-Zuluaga (2023) effectively applied SHAP to ML-based demand forecasts, indicating which elements—such as promotions, seasonality, or particular marketing campaigns—were the main causes of a forecasted demand increase or decrease. In a similar vein, Jahin et al. (2024) created a hybrid CNN-LSTM-GRU model that included SHAP analysis. By exposing the global significance of different features, they were able to achieve both high accuracy and a certain amount of transparency. These methods' emphasis on static, post-prediction explanations, however, is a major drawback; while they address the "what" that led to the forecast, they frequently fall short of offering the "so what"—actionable insights or alternate scenarios that planners require in order to make decisions.

A more sophisticated line of research has started to examine how explainability is framed within the particular decision-making environment of supply chain management in order to go beyond static explanations. Zhu et al. (2025) created a user-centric explainability paradigm specifically designed for demand planning, which was a major conceptual advance. According to their work, an explanation must be directly related to operational choices like staffing levels, transportation scheduling, or inventory replenishment in order to be considered valuable. Their framework clearly has room for improvement, as it mainly stays conceptual and lacks a real-world, implemented model that demonstrates these capabilities, even though it successfully lays out the requirements for actionable explanations, such as the necessity of counterfactual queries and "what-if" simulations.

Simultaneously, scientists have worked to improve deep learning models' inherent interpretability when applied to sequential demand data. One step in this approach is the work done by Zhou and Wang (2023) on an LSTM model for purchase prediction that has been improved using attention processes. A type of temporal explainability is provided by attention weights, which can graphically show which prior time-steps (such as particular weeks or days) had the greatest impact on producing the forecast. By demonstrating to planners, for instance, that the model is strongly weighting the promotional period from the previous quarter, this somewhat allays the black-box fear. However, a drawback identified in their and related research is that, despite its value, this temporal insight still does not easily convert into interactive scenario planning or prescriptive decision assistance, both of which are essential for strategic supply chain management.

There is a clear research gap that completely integrates forecasting with prescriptive, decision-centric explanations, despite the field's impressive progress in introducing basic explainability and improving model accuracy, according to a critical review of the body of existing literature. The majority of previous publications, including those by Arboleda-Florez and Castro-Zuluaga (2023) and Nair and Subramanian (2022), either emphasize accuracy or offer descriptive rather than prescriptive explanations. The state-of-the-art does not yet have a unified system that can simultaneously produce counterfactual explanations ("If promotion X did not exist, demand would be Y% lower"), provide a highly accurate forecast, and facilitate dynamic "what-if" simulations ("What is the forecasted impact of a 10% price increase?"). This disparity highlights the necessity of the proposed study, which seeks to expand on previous earlier studies by creating a XAI-driven framework that clearly connects demand projections to practical supply chain choices, thereby transcending simple number-crunching and producing strategic insights.

2.3.1 Traditional Demand Forecasting and the Black-Box Problem

Demand forecasting in supply chains was mostly dependent on statistical techniques and traditional time-series analysis prior to the use of sophisticated AI. Because of their well-understood mathematical underpinnings, techniques like Auto-Regressive Integrated Moving Average (ARIMA), exponential smoothing, and linear regression served as the foundation of planning systems and offered a baseline of interpretability (Nair & Subramanian, 2022). Although these models laid a crucial basis for inventory and logistics planning, they are essentially limited in their ability to identify intricate, non-linear patterns in demand data that are influenced by a variety of complicated events, including market movements, competitor activity, and promotions.

Advanced machine learning and deep learning models, such as XGBoost, Random Forests, and Long Short-Term Memory (LSTM) networks, have been widely experimented with and used in an effort to increase predicting accuracy. These models demonstrated superior performance in identifying intricate relationships within historical data, often significantly outperforming their statistical predecessors. However, a significant loss in interpretability was the price paid for this accuracy boost. According to Zhu et al. (2025), models such as LSTM and complex ensembles function as "black boxes," meaning that a human planner cannot see the internal logic that links inputs to the final forecast.

In real-world situations, this opacity significantly reduces trust. Those in charge of inventory, transportation, and procurement choices, supply chain managers and planners, are frequently hesitant to act on projections whose logic they do not understand or can not defend. For example, it is challenging to align resources appropriately when a planner is unable to explain to a logistics manager why an LSTM model projected a 30% jump in demand for a certain product. Without context, the model's result is just a number, leaving open important concerns about which driving forces had the most impact or how the projection would alter in various business scenarios. The need for Explainable AI (XAI) solutions has been sparked by the discovery that a significant obstacle to the full potential of AI in supply chain management is the fundamental discrepancy between model performance and practical usability.

2.3.2 Post-hoc Explainable AI (XAI) for Demand Forecasting

Research on using post-hoc Explainable AI (XAI) strategies to demystify forecasts has increased significantly since the "black-box" problem in sophisticated forecasting models was identified. After a prediction is generated, these techniques examine the input-output links in the complicated model to produce explanations that are understandable to humans, without changing the underlying model itself. By giving planners an understanding of the "why" behind a forecast, the main objective is to close the trust gap and make high-accuracy models like XGBoost and LSTM more acceptable for use in practical decision-making.

One well-known and often used method in this field is SHAP (SHapley Additive exPlanations). SHAP measures each input feature's contribution to a particular forecast using game-theoretic principles. For example, in a direct sales setting, Arboleda-Florez and Castro-Zuluaga (2023) successfully implemented SHAP to an ML-based demand forecasting system. Their research showed how SHAP values might provide a clear split of the components that influenced an anticipated demand surge, indicating whether it was mostly caused by a recent promotion, seasonal tendencies, or particular marketing initiatives. This method offers global insights into the behavior of the entire model as well as local explanations for specific predictions.

Researchers have furthered this line of work by directly integrating XAI with intricate deep-learning architectures. For instance, Jahin et al. (2024) used SHAP analysis in their hybrid CNN-LSTM-GRU model for demand forecasting. Their approach, which used SHAP to reveal the worldwide significance of a number of factors, including price, weather, and economic indicators, obtained high predicted accuracy. This encouraged the adoption of increasingly complex models by proving that accuracy and a certain amount of transparency are not mutually contradictory objectives.

Nevertheless, the descriptive and static nature of these post-hoc methods is a major drawback. Although they successfully handle the "what" aspects that were crucial, they frequently fail to address the "so what" for a supply chain planner. Although the explanations are retrospective and provide justification for a specific predicted figure, they are unable to interactively examine other possibilities or suggest practical solutions. The need for planners to have dynamic insights that can directly guide decisions on inventory, promotions, or logistics creates a gap between operational utility and technical explainability. The subsequent development in XAI research, which focuses on practical and decision-centric explanations, has been sparked by this weakness.

2.3.3 Actionable and Decision-Centric Explanations in Supply Chains

A more sophisticated field of study concentrates on producing explanations that are immediately applicable in the context of supply chain decision-making, even when post-hoc XAI techniques offer insightful information on model thinking. This paradigm change goes beyond explaining the nature of a forecast to show how it might guide certain operational choices like arranging transportation, inventory replenishment, or promotional campaigns.

Converting forecasts from passive data into useful instruments for strategic intervention is the main goal.

Zhu et al.'s user-centric explainability framework is a noteworthy conceptual breakthrough in this field (2025). According to their study, an explanation needs to be causally connected to levers that planners can control in order to be genuinely useful in demand planning. They explicitly stated that counterfactual questions, like "What would the demand be if the lead time were reduced by two days?" require explanations. —and interactive "what-if" models that let planners test the effects of possible business choices before making them. This paradigm provides a crucial road map for connecting managerial action with data science outcomes.

One important technical strategy for accomplishing this objective is the creation of counterfactual explanations. These explanations make the logic of the model prescriptive by responding to "what if" scenarios by modifying input features significantly and then observing the change in the forecast. A system might, for example, produce a counterfactual that reads, "If promotion X did not exist, the demand forecast would be 15% lower," which would directly affect the marketing activity's worth. Likewise, a statement such as "Stockouts can be reduced by 20% if safety stock is increased by 100 units," establishes a direct and measurable connection between an inventory choice and the forecast. This transforms explanation into a proactive planning tool rather than a descriptive post-mortem.

The fact that many of these frameworks, like the one by Zhu et al. (2025), are still primarily conceptual or are only used in controlled experimental settings is a significant drawback of the state-of-the-art. Though they frequently lack a fully developed, integrated system that exhibits these capabilities on an actual, end-to-end forecasting and planning platform, they are successful in defining the needs for actionable explanations. Making sure these dynamic explanation modules are both computationally efficient and easy for planners to use while integrating them seamlessly into current supply chain management workflows is the challenge. This discrepancy between the theoretical framework and scalable, real-world implementation points to a crucial area that needs more work.

2.3.4 Inherently Interpretable Deep Learning for Temporal Data

Creating deep learning models with inherent interpretability is a research avenue that runs concurrently with post-hoc explanation techniques, especially for sequential demand data. This method aims to provide more transparent and intuitive insights, particularly with regard to time-based patterns, by integrating explainability directly into the model's architecture rather than considering it as an external add-on. In supply chain scenarios, knowing when significant events impacted a forecast is just as vital as knowing what those events were.

Integrating attention mechanisms with recurrent neural networks, such as LSTMs, is a key method in this category. The model may successfully emphasize the precise time steps that had the greatest influence on a particular prediction by using attention processes to give each input in a sequence a weight. Zhou and Wang (2023), for instance, created an LSTM model for purchase prediction that incorporates an attention mechanism. Their work showed that the model may provide a direct form of temporal explainability by visually indicating to a planner that the forecast was significantly influenced by a particular week of strong sales or the promotional time from the previous quarter.

Because it aligns the internal reasoning process of the model with the natural thought process of a planner, this intrinsic interpretability provides a substantial benefit over post-hoc methods. Rather than a complicated SHAP analysis, a planner can be shown a straightforward heatmap or timeline that highlights the past data periods that the model "paid attention to." Because it demystifies the model's dependence on historical occurrences and occasionally reveals previously hidden temporal relationships, this can instantly foster trust.

However, a significant drawback is that, despite its value, this temporal insight frequently stays descriptive rather than prescriptive, as noted in Zhou and Wang's (2023) study and related investigations. The attention mechanism does not automatically produce interactive "what-if" scenarios or directly recommend actions, but it can demonstrate the significance of last month's promotion. It cannot, for example, automatically respond to a planner's inquiry regarding the possible effects of moving a future promotion to a different week. The insight falls short of the dynamic, forward-looking decision assistance needed for strategic supply chain management since it is limited to describing the historical drivers of a single forecast. This emphasizes that although naturally interpretable models increase transparency, their full decision-centric utility requires integration with other XAI and simulation techniques.

2.3.5 The Integration Gap : From Predictive Accuracy to Prescriptive Insights

A distinct path from merely statistical models to high-accuracy AI and then to fundamental explainability can be seen in the changing demand forecasting landscape. Nonetheless, there is still a big integration gap between producing genuinely prescriptive, decision-centric insights for supply chain management and producing precise, explicable forecasts. The existing state-of-the-art frequently views post-hoc explainability, actionable scenario planning, and forecasting accuracy as distinct problems, resulting in a disjointed toolkit that is unable to offer a cohesive platform for strategic planning. A hybrid XAI framework that smoothly combines these capabilities into a single, integrated system is necessary to close this gap.

Such interconnected systems are essential, according to recent study. Zhu et al.'s conceptual framework from 2025 specifically calls for explanations linked to operational decisions, but like other work in the field, theirs lacks a proven, end-to-end implementation. Likewise, whereas post-hoc techniques like SHAP (Arboleda-Florez & Castro-Zuluaga, 2023) offer feature-level breakdowns and models with inherent interpretability, such attention-based LSTMs (Zhou & Wang, 2023), offer useful temporal insights, they function independently. Thus, a planner is left to mentally combine these different explanations—the "what" from SHAP and the "when" from attention—and manually relate them to "what-if" scenarios, which is a laborious and error-prone process.

Three integrated layers would be included in a suggested architecture for a unified system:

- Prediction Layer: Baseline demand estimates are produced by high-performance models (such as XGBoost and LSTM ensembles).

- Multi-Modal Explanation Layer: This layer provides a thorough justification for the prediction by simultaneously using intrinsic approaches (e.g., attention for temporal importance) and post-hoc techniques (e.g., SHAP for feature importance).

- Planners can interactively test the effects of price, promotion, or lead time adjustments on the forecast by using the Prescriptive Simulation Layer, a critical component that uses the explanations to create dynamic counterfactuals and "what-if" simulations.

The computational and architectural complexity of smoothly integrating these layers together is the main obstacle to achieving this objective. Although each component has been thoroughly studied, it is still unclear how to combine them into a platform that is both user-friendly and computationally efficient for supply chain planning in the real world. There is a trade-off between the system's latency and scalability for enterprise-level use and the amount of simulation and explanation. As a result, the important research objective now includes designing and implementing a comprehensive XAI-driven framework that turns demand projections from static data into a dynamic engine for strategic decision-making, rather than merely improving individual components.

2.3.6 Comparative Evaluation of XAI Approaches for Demand Forecasting

The several Explainable AI (XAI) techniques used for demand forecasting, ranging from post-hoc analysis to naturally interpretable models, each have unique advantages and disadvantages, as shown by a critical review of the literature. The current maturity of explainable forecasting systems is revealed by evaluating these approaches along several important dimensions, including explanatory depth, actionability, integration complexity, and end-user trust. This evaluation also identifies the specific gaps that the proposed research seeks to fill.

Explanatory Depth

Post-hoc methods like as SHAP are excellent at offering detailed, feature-level explanations and measuring how much each unique input—like pricing or promotions—contributes to a particular forecast (Arboleda-Florez & Castro-Zuluaga, 2023). On the other hand, models that are inherently interpretable, such as attention-based LSTMs, provide superior temporal depth by indicating the times when historical events had the greatest impact (Zhou & Wang, 2023). Nevertheless, neither approach alone offers a comprehensive view; attention mechanisms frequently lack precise feature attribution, and SHAP lacks temporal context.

Actionability for Decision-Making

An explanation's capacity to influence choices is its greatest asset. Although there are conceptual frameworks for decision-centric XAI (Zhu et al., 2025), they are still not widely used. Post-hoc explanations lack prescriptive "what-if" powers and are static and descriptive. Although models that are naturally interpretable offer transparency, they do not automatically produce counterfactual possibilities, which leaves supply chain planners with a large gap in immediately useful information.

Integration Complexity

One of the biggest challenges is integrating XAI into current planning workflows. Although post-hoc techniques like SHAP are relatively simple to include into pre-existing black-box models, they require users to complete two steps. Redesigning the forecasting pipeline from the ground up is necessary to create models that are intrinsically interpretable. Widespread adoption is significantly hampered by the architectural complexity and computational demands of a fully integrated system that combines interactive simulation, multifaceted explanations, and high accuracy.

End-User Trust and Adoption

Trust is influenced by usefulness and relevance as well as technical explainability. While the simplified visualizations of attention mechanisms may be more intuitive but less quantitatively accurate, planners may find the SHAP outputs excessively technical and disconnected from their operational reality. Systems that enable planners to interactively verify their decisions and immediately connect explanations to business levers are likely to attain the maximum level of trust a capacity that is currently underutilized in the literature.

Approach	Explanatory Depth	Actionability	Integration Complexity	Key Limitations
Post-hoc (e.g., SHAP)	High (Feature-level)	Low (Descriptive only)	Low (Add-on)	Static output, no "what-if" capability
Inherently Interpretable	Medium (Descriptive only)	Low (Descriptive only)	High (Model-specific)	Lacks feature-level quantification
Conceptual Decision-	High (Theoretical)	High (Theoretical)	Very High	Lacks implemented,

Centric Frameworks				end-to-end systems
Proposed Hybrid XAI Framework	High (multi-faceted)	High(prescriptive)	Very High	Architectural and computational complexity

2.4 Dataset Selection

The demand forecasting models and the Explainable AI (XAI) components that go along with them must be trained and validated using the right datasets. This study uses a hybrid dataset strategy that combines synthetic feature generation, proprietary industrial data, and publically available retail data. This guarantees that a variety of causative elements, realistic demand patterns, and complex circumstances where explainability is most important are all introduced into the models.

- Public Retail Datasets (M5, Favorita): Offering extensive, historical time-series data on unit sales, pricing, and promotional calendars for a variety of product categories and retail locations are the M5 Competition dataset and the Corporación Favorita supermarket sales data. These datasets provide a solid foundation for training fundamental forecasting models and comparing the explainability and performance of various algorithms to accepted industry norms.

- Proprietary Supply Chain Data: An industrial partner's proprietary dataset will be used to anchor the research in actual operational difficulties. This dataset contains comprehensive records of lead times, inventory levels, product demand, and logistical information (such as delivery schedules and modes of transportation). This makes it possible to create and evaluate XAI justifications that are closely related to certain supply chain choices, such as transport scheduling and inventory replenishment.

- Synthetic Feature Generation: Programmatic creation of synthetic features will be used to thoroughly test the "what-if" simulation and counterfactual explanation skills.

This entails developing believable variations for important decision levers including marketing spend levels, competitor price indices, weather events, and special discounts (e.g., 5%, 10%, 15% off), which may not be fully represented in previous data.

- Event Annotation: "Black Friday," "Supplier Disruption," and "New Product Launch" are examples of labels that will be used to tag historical data. This annotation is essential for verifying the temporal insights offered by methods such as attention processes and assessing how well the XAI system can recognize and ascribe the significance of important events in its explanations.

The study guarantees thorough dataset coverage by integrating event annotations, synthetic scenario development, proprietary operational data, and public benchmarks. The suggested XAI-driven forecasting methodology for actual supply chain management is more robust, generalizable, and practically relevant thanks to this multifaceted approach.

2.5 Benchmarking and Evaluation

Assessing the efficacy, interpretability, and usefulness of demand forecasting systems enhanced with Explainable AI (XAI) requires benchmarking and evaluation. Benchmarking offers an organized way to contrast the suggested XAI-driven framework with conventional forecasting techniques in the context of this study. Forecasting accuracy, explanation quality, computational efficiency, and decision-making impact are usually taken into account in evaluation frameworks. It is feasible to show how well the suggested approach fills the actionability and trust gaps in supply chain planning by utilizing both quantitative and qualitative evaluation methods.

2.5.1 Benchmarking Framework

Three main dimensions serve as the guidelines for benchmarking in this study:

1. Forecasting accuracy, as determined by conventional error measures, is the model's ability to predict future demand.

- (MAPE) = (1/n) * Σ |(Actual - Forecast)/Actual| * 100 means the mean absolute percentage error.

- RMSE, or root mean squared error, is equal to $\sqrt{[\ \Sigma(\text{forecast - actual})^2 / n\ ]}$.

- Σ|Actual - Forecast| / Σ|Actual| is the Weighted Absolute Percentage Error (WAPE) formula.

2. Both technical metrics and user-centric evaluations are used to measure the quality and actionability of the explanation:

- The degree to which the explanation accurately captures the logic of the model is known as explanation fidelity (e.g., utilizing log-odds or probability changes for SHAP).

- Decision-Support Score (DSS): A qualitative score (1–5) determined by subject-matter experts that evaluates the degree to which an explanation influences a particular supply chain action (e.g., promotion planning, inventory order).

- Compared to a baseline, scenario planning efficiency is the amount of time it takes a planner to make a choice after analyzing the prediction and its justifications.

3. Computational Performance is measured in order to benchmark:

- Training Time: The amount of time needed to train the XAI components and the main forecasting model.

- Inference Time: The amount of time needed to produce a forecast and the justifications for it.

- "What-if" The time it takes to create a counterfactual situation is known as the simulation latency.

2.5.2 Comparative Evaluation

Although they offer a baseline of interpretability, traditional statistical models (like ARIMA) frequently have higher forecast errors (MAPE > 15% for complex categories, for example). High-accuracy black-box models (like LSTM and XGBoost) can lower MAPE to less than 10%, but they don't have any built-in justifications, which makes planners less likely to trust and use them. Although current XAI-enhanced models (such as LSTM with SHAP) increase transparency, they frequently lack integrated scenario planning and generate explanations slowly, which results in a modest Decision-Support Score.

It is anticipated that the suggested framework, which combines prescriptive simulation with multi-modal explanations, will greatly increase explanation utility (goal DSS > 4/5) and achieve excellent predicting accuracy (target MAPE < 8%). The possible increase in inference and simulation latency, which will be tuned for near-real-time application, is a significant trade-off.

A benchmark table that contrasts several methods would look like this:

Metric	Traditional (ARIMA)	Black-Box (LSTM)	XAI-Enhanced (LSTM+SHAP)	Proposed XAI Framework
Forecast Accuracy (MAPE%)	15-20%	8-12%	8-12%	< 8% (Target)
Interpretability	High	None	Medium	High (multi-faceted)
Decision-Support Score (1-5)	3	1	2	4 (Target)
Inference Time (ms)	< 100	200	500	700 (Target)

"What-if" Capability	Manual	None	None	Integrated

2.5.3 Critical Reflection

Despite their interpretability, benchmarking results demonstrate that classical models are inadequate for capturing intricate, contemporary demand patterns. Although black-box models are accurate, their lack of trust renders them operationally useless. Although they provide a compromise, the current XAI-enhanced models fall short of bridging the gap to decision-making since they are descriptive rather than prescriptive.

The suggested framework combines high accuracy with interactive scenario planning and practical, multi-modal explanations to establish itself as a decision-support system rather than merely a forecasting tool. Higher adoption potential and measurable business benefit are demonstrated by this dual capability. Thus, benchmarking highlights the originality of this research and verifies its contribution to filling the key integration gap between supply chain decision-making and forecasting.

2.7 Chapter Summary

The literature on supply chain management's use of Explainable AI and demand forecasting has been thoroughly reviewed in this chapter. It recognized the fundamental issue of high-performing models' "black-box" nature and the crucial juncture between forecasting and actionable insights. The assessment concluded with the discovered integration gap after discussing post-hoc XAI techniques, classic forecasting methods, naturally interpretable models, and the new field of decision-centric explanations. Evaluation frameworks, benchmarking criteria for explainability and accuracy, and the significance of datasets were also covered. These insights will inform the next study approach, which will be tailored to fill the gaps and direct the creation of a unified, XAI-driven framework that turns demand projections into supply chain optimization prescriptive tools.

Chapter 03: Methodology

3.1 Chapter Overview

The thorough methodology used for this research endeavor is described in this chapter. In order to methodically handle the research objectives, it will go into detail about the development framework, project management strategy, and research technique. In order to achieve the project's objectives of developing an interpretable demand forecasting system for supply chain management, the chapter will outline the procedures for data preparation, model development, Explainable AI (XAI) deployment, and assessment metrics.

3.2 Research Methodology (Saunders' Research Onion in Table Form)

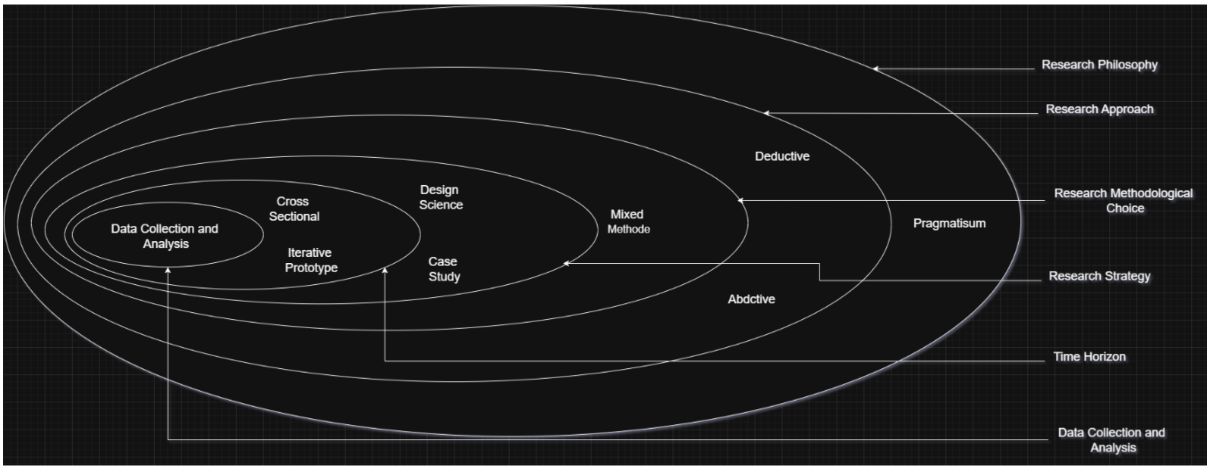


Figure 1 : Onion Chart

Layer	Choice	Justification
Philosophy	Pragmatism	In order to assess both the technical and human-centric aspects of XAI in supply chains, pragmatism encourages the use of quantitative techniques (model accuracy metrics, forecasting mistakes) with

		qualitative evaluation (planner trust, explanation usefulness).
Approach	Deductive with Abductive Elements	Proven notions of XGBoost, LSTM, and XAI methods are tested in this deductive study. The best explanations and "what-if" scenarios that fit planners' decision-making logic are deduced through abductive reasoning.
Methodological Choice	Mixed Methods (Quantitative + Qualitative)	Forecasting accuracy (MAPE, RMSE) and computational performance are assessed quantitatively. To evaluate the actionability and reliability of the XAI explanations, qualitative techniques like expert surveys and usability testing are essential.
Strategy	Design Science & Case Study	The new XAI-driven forecasting artifact is developed and thoroughly tested using the Design Science methodology. The usefulness of the framework in a particular supply chain environment is validated in a real-world setting through a

		Case Study with an industry partner.
Time Horizon	Cross-sectional with Iterative Prototyping	The study is carried out according to a cross-sectional project timeframe. However, an iterative prototyping approach is used for the model development and integration of the XAI components in order to gradually improve the system based on feedback and performance.
Data Collection & Analysis	Mixed-Method (Secondary & Synthetic Data)	Public benchmarks are provided by secondary datasets (like M5), while real-world complexity is provided by confidential industrial data. Comprehensive scenarios are created via synthetic data creation to test "what-if" simulations and counterfactual explanations.

3.3 Development Methodology

3.3.1 Requirement Elicitation Methodology

A multifaceted elicitation process was used to make sure the system requirements appropriately address both technical performance and real-world usability in supply chain scenarios. These methods ensured that the final requirements would close the gap between accurate forecasting and useful decision support by offering a variety of viewpoints from technical and business stakeholders.

Interviews: To learn about supply chain planners', logistics managers', and inventory analysts' present forecasting workflows, black-box model pain points, and particular decision-making procedures, structured conversations were held with them. This made it easier to pinpoint important elements for justifications, like the necessity of lead-time sensitivity and promotion impact assessments.

Surveys: To collect quantitative information on preferred explanation styles, trust factors, and the most useful "what-if" scenarios, questionnaires were sent to a larger group of possible end users from various manufacturing and retail firms. This guaranteed that the interpretability features of the system would be broadly applicable and user-centric.

Document Analysis: Academic literature on XAI evaluation, forecasting reports, and documentation from supply chain management systems were examined. This facilitated the understanding of the technological limitations for integration into current corporate systems, the establishment of performance standards, and the identification of functional gaps in present solutions.

Brainstorming: To improve system features, cooperative workshops were conducted with data scientists, supply chain specialists, and software architects. These workshops generated creative concepts for creating user-friendly interfaces for the prescriptive simulation layer and striking a balance between explainability and model complexity.

Self-Evaluation: To confirm that the requirements were coherent, comprehensive, and feasible, a critical self-assessment was conducted on a regular basis. The main research issue of establishing confidence and actionability was addressed by this iterative process, which also helped prioritize features and guarantee the final requirement set was strong.

All things considered, the combination of these techniques guaranteed a thorough requirements elicitation process that combined in-depth technical knowledge with end-user usefulness. This has established a solid basis for creating a system that is useful for supply chain planning in the real world, accurate, and adaptable.

3.3.2 Design Methodology

This system uses the Object-Oriented Analysis and Design Methodology (OOADM), which makes it possible to model intricate forecasting and explanation components as interacting objects, resulting in an architecture that is modular, extensible, and maintainable. OOADM makes ensuring the system can adjust and integrate new models or XAI techniques without requiring a complete redesign, since demand forecasting and explanation demands may vary as business conditions do.

OOADM's advantages for the system

- **Modularity:** By being created as separate entities, core components (such as Forecasting Engine, XAIInterpreter, and Scenario Simulator) make creation, testing, and maintenance easier.

- **Reusability:** Data Source, Forecast Model, and Explanation are examples of foundational objects that can be utilized by various forecasting pipelines and explanation modules.

- **Scalability**: Concurrent "what-if" simulation requests and massive amounts of historical demand data are effectively handled by the object-oriented structure.

- **Flexibility:** New XAI techniques or forecasting algorithms (such as deep learning architectures) can be incorporated as new classes without impairing the operation of the current system.

- **Clear Modelling:** UML diagrams, such as class and sequence diagrams, help developers and stakeholders understand how items like the Demand Planner and the Explanation Generator interact with one another.

3.3.3 Programming Paradigm

Because OOP places a strong emphasis on modularity, code reuse, and scalability, the system will follow its principles. OOP makes it possible to describe important things as objects with enclosed data and behaviors, like Time Series, Forecast, SHAP Explainer, and Counterfactual Scenario. The codebase is well-structured and easy to use thanks to this abstraction. To facilitate smooth system evolution, new classes that build upon or combine with preexisting explanation types or forecasting models might be introduced. The main implementation language will be Python, which makes use of its robust machine learning (Scikit-learn, XGBoost, TensorFlow), data science (Pandas, NumPy), and specialized XAI libraries (SHAP, LIME) ecosystems to ensure the successful integration of complex models within a clear, object-oriented framework.

3.3.4 Testing Methodology

A thorough and organized testing technique will be used to guarantee the XAI-driven demand forecasting system's dependability, accuracy, and usefulness. The forecasting models' predictive capabilities as well as the caliber and usability of the explanations produced by the XAI components will be the main subjects of testing. Since forecast accuracy and interpretability play a major role in supply chain decisions, it is essential to thoroughly evaluate the models and make sure the integrated prototype provides end users with logical, useful insights.

- To assess the effectiveness of the main forecasting algorithms (such as XGBoost and LSTM), model testing will be done. To assess forecasting precision, important measures including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Weighted Absolute Percentage Error (WAPE) will be examined. Concurrently, the XAI components will be assessed for Robustness, which guarantees that explanations stay constant for comparable input scenarios, and Explanation Fidelity, which gauges how accurately the explanations (such as attention weights and SHAP values) represent the model's internal thinking.

- The end-to-end integrated system will subsequently be evaluated through prototype testing. To guarantee smooth data flow between modules—such as the forecasting engine, the XAI interpreter, the scenario simulation layer, and the data preprocessing pipeline—integration testing will be used. Additionally, supply chain planners will participate in usability testing to confirm that the explanations and "what-if" scenarios provided are understandable, pertinent, and actionable. Prior to any real-world implementation, this phase will evaluate the system's overall decision-support capacity, interface usability, and performance in order to discover any practical issues.

This methodology guarantees that the resulting framework is not only statistically accurate but also reliable, easy to use, and truly beneficial for improving supply chain decision-making processes by fusing thorough model-level validation with comprehensive system-level testing.

3.3.5 Solution Methodology

The solution methodology outlines the methodical process for creating the supply chain management framework for XAI-driven demand forecasting. This comprehensive procedure guarantees that the finished product produces precise forecasts and clear, useful justifications that planners can rely on and use to guide their decisions. Data collection, preprocessing, feature engineering, model creation, XAI integration, and continual improvement are all included in the methodology.

1. **Dataset Collection**

   The acquisition of extensive datasets that accurately depict supply chain demand patterns and affecting factors is the basis of this study. This project employs a hybrid methodology, integrating proprietary industrial supply chain data with publicly accessible benchmark datasets, such as the M5 competition data. Historical sales data, calendars of promotions, pricing details, inventory levels, and outside variables like holiday schedules are all included in these datasets. In order to evaluate XAI's capabilities, particular "what-if" scenarios will be created using synthetic data, which will guarantee that the framework can manage a range of operating settings and offer pertinent counterfactual explanations.

2. **Data Preprocessing**

   Inconsistencies, missing values, and temporal misalignments are common in raw supply chain data, which might impair model performance. Preprocessing is cleaning the data by aligning all time series to a consistent frequency (e.g., daily or weekly), eliminating outliers, and addressing missing values by interpolation. Using the proper methods, categorical variables like product categories, store locations, and promotion types are encoded. To facilitate thorough model evaluation and avoid overfitting, the dataset is subsequently divided into training, validation, and testing sets.

3. **Feature Selection and Engineering**

   Capturing the intricate drivers of demand requires effective feature engineering. Lagged demand figures, rolling data (such as the 7-day moving average), promotional indications, price elasticity metrics, seasonality markers, and external economic indicators are some of the salient characteristics. The most predictive features are determined using feature selection methods like mutual information score and SHAP analysis, which lower dimensionality and increase model training effectiveness while also serving as the fundamental inputs for the XAI explanations.

4. **Model Selection**

   To strike a compromise between explainability and predictive capability, a hybrid modeling technique is used. The main benchmark for their excellent performance and suitability for SHAP explanations is Gradient Boosting Machines (XGBoost). In order to capture temporal dependencies, Long Short-Term Memory (LSTM) networks with attention mechanisms are used. Attention weights provide intrinsic interpretability. At this point, the XAI framework is integrated, setting up SHAP for post-hoc explanations and creating the counterfactual engine for the creation of "what-if" scenarios.

5. **Model Training**

   With careful hyperparameter adjustment, the preprocessed datasets are used to train the chosen models. Cross-validation is used to optimize XGBoost's parameters, including regularization, tree depth, and learning rate. Attention layers are added to LSTM models, and variables like attention dimensions, dropout rates, and hidden units are adjusted. In particular, distinct validation sets are kept up to date during the training process to check for overfitting and guarantee generalization across various product categories and time periods.

6. **Testing**

   Both predicting accuracy and explanation quality are evaluated using a thorough evaluation framework. Metrics like MAPE, RMSE, and WAPE are used to gauge forecasting performance. Quantitative metrics (explanation integrity, stability) and qualitative evaluation through supply chain planner user studies are used to analyze the XAI components. The testing stage confirms that the system can produce precise estimates and offer logical, useful justifications for a variety of situations, such as demand shocks and promotional events.

7. **Feedback Loop**

   The last element creates a process for ongoing learning in which planner input regarding the value of the explanation and the precision of the forecast is methodically gathered. Periodically, the model is retrained and the explanation is improved as a result of this feedback and fresh demand data. Based on planner preferences and real-world usage patterns, this adaptive approach continuously enhances the system's explanations' relevance and actionability while guaranteeing that it stays correct as market conditions change.

3.4 Project Management Methodology

The Agile technique has been chosen as the project management strategy for this undertaking. Agile's emphasis on iterative development, flexibility, and ongoing input makes it more appropriate than more conventional approaches like Waterfall. Agile offers the flexibility required to provide an efficient and user-centric solution because creating a XAI-driven forecasting system entails testing out various models, improving explanatory interfaces, and adjusting to changing user needs.

- Iterative Development: Tasks are broken down into brief sprints, each of which focuses on a particular aspect, like UI design, XAI integration, model development, or data preprocessing. Every iteration produces a system increment that can be tested.

- Flexibility: When new information is revealed by model performance, user input on explanations, or shifting supply chain priorities, the Agile methodology permits modifications to be made at any point during the project lifecycle.

- Constant Feedback: The forecasting accuracy and the actionability of the XAI explanations are improved by regular reviews with stakeholders and possible end users (supply chain planners).

- Risk Reduction: By gradually creating and verifying essential features, the project lowers the possibility of significant malfunctions and guarantees that the finished system firmly combines explainability and forecasting.

- Collaboration: Agile ensures that technological development stays in line with the real-world requirements of supply chain management by encouraging tight teamwork and continuous communication between data scientists, software engineers, and domain specialists.

In conclusion, Agile was selected due to its ability to facilitate experimentation, adapt to change, and encourage continuous improvement—all of which are critical for developing a reliable and realistic demand forecasting system with integrated explainable AI.

3.4.2 Schedule

3.4.2.1 Gantt Chart

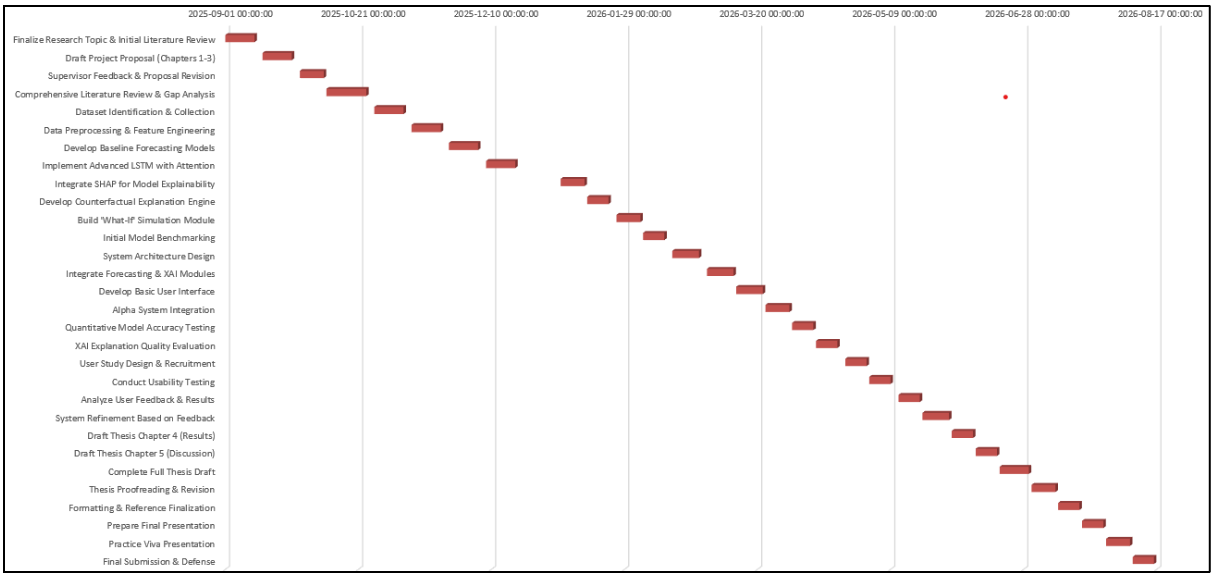


Figure 2 : Gantt Chart

3.4.2.2 Deliverables

Deliverables	**Dates**
Project Proposal	10th Sep 2025
Literature Review	10th Sep 2025
Software Requirement Specification	25th Sep 2025
Project Proposal – initial draft	26th Sep 2025
Project Proposal and Requirement Specification – final draft	24th Oct 2025
Project Proposal and Requirement Specification – Final	14th Nov 2025
Proof of Concept	14th Nov 2025
Design Document	
Prototype	2nd Feb 2026
Interim Project Demo	2nd Feb 2026
Implementation	25th Feb 2026

Testing	1st Mar 2026
Evaluation	28th Mar 2026
Thesis Submission	1st Apr 2026
Minimum Viable Product	1st Apr 2026
…..	

3.4.3 Resource Requirements

Suitable hardware infrastructure for computationally demanding model training and real-time inference, specialized software tools and frameworks for implementing AI models and XAI components, extensive datasets representing a variety of demand patterns and supply chain scenarios, and multidisciplinary technical skills in machine learning, time series analysis, and supply chain management are among the resources required to successfully implement and validate the integrated framework. These requirements are based on the project's functionalities and objectives.

3.4.3.1 Data

Data from various sources will be gathered for this study in order to train and assess the XAI components and demand forecasting models. While the Favorita Grocery Sales dataset will offer more temporal information, the M5 Competition dataset will include entire retail sales data with promotional calendars and product hierarchies. To replicate different supply chain scenarios and edge cases, synthetic data will be produced.

To improve contextual understanding, external datasets on weather patterns and economic indicators will be included. Together, these resources will build a strong data environment that will enable precise demand forecasting and significant, explainable AI applications.

3.4.3.2 Skills

Effective creation of this system necessitates a blend of domain-specific, technical, and analytical skills. These abilities guarantee the effective application of XAI components, forecasting models, and their incorporation into workable supply chain solutions.

Skill	**Justification**

Machine Learning & Deep Learning	for putting advanced neural architectures into practice and creating and refining forecasting models (XGBoost, LSTM).
Python Programming & Data Science	for developing models, putting data pipelines into practice, and making use of libraries like TensorFlow, Pandas, and Scikit-learn.
Explainable AI (XAI) Techniques	for using attention mechanisms, SHAP, and LIME to produce comprehensible justifications for forecasting results.
Time Series Analysis & Forecasting	vital for analyzing temporal data, finding trends, and creating precise prediction models.
Supply Chain Management Knowledge	essential for determining pertinent measurements, comprehending domain context, and guaranteeing that solutions are practically applicable.
Data Visualization & Dashboard Development	for developing user-friendly interfaces that successfully convey projections and justifications to business users.
Cloud Computing & MLOps	permits continuous forecasting system integration and delivery, model serving, and scalable deployment.
Statistical Analysis & Experimental Design	need for thorough model assessment, hypothesis testing, and explanation quality validation.
Agile Project Management	guarantees iterative development, flexible planning, and productive cooperation between domain and technical teams.

3.4.4 Risk and Mitigation

To guarantee successful implementation, a XAI-driven demand forecasting framework for supply chain management must be developed. Project execution will go more smoothly if possible obstacles are proactively addressed from technical, data-related, and adoption viewpoints. The following table lists the hazards that have been identified, along with their frequency, severity, and associated mitigation techniques.

Risk	**Severity**	**Frequency**	**Mitigation Strategy**
Inaccurate Forecasting Models	4	3	Apply rigorous hyperparameter tuning, model ensembles, and ongoing validation against a variety of accuracy measures (MAPE, RMSE).
Poor Quality or Insufficient Data	4	3	Make use of advanced data imputation and augmentation techniques, as well as hybrid datasets (public, proprietary, and synthetic).
Computational Complexity of XAI	3	4	Use cloud scaling for complex calculations and optimize explanation algorithms (e.g., approximation SHAP techniques).
Low User Trust in Explanations	3	3	Create user-friendly visuals that are suited to various user roles and test usability iteratively with planners.
Integration Challenges with Existing SCM Systems	3	2	To facilitate interoperability, create standardized APIs for integration and use a modular system architecture.
Resource Intensive Model Training	2	4	Implement effective data pipelines, model checkpointing, and cloud-based GPU resources.

3.5 Chapter Summary

The thorough approach and structure used to create the supply chain management XAI-driven demand forecasting system have been described in this chapter. In order to guarantee reliable and useful results, it described the study philosophy and methodology in depth, outlining the collection and analysis of both quantitative and qualitative data. The technological design, including the use of forecasting models and XAI components and their integration into a coherent framework, was guided by the development approach. A organized and iterative roadmap for effectively and efficiently achieving the study objectives was also provided by the project management methodology, which included established the project's scope, timeframe, resource allocation, and risk management techniques.

Chapter 04: Software Requirement Specification (SRS)

4.1 Chapter Overview

A thorough and organized Software Requirement Specification (SRS) is provided in this chapter for the "Explainable AI-Driven Demand Forecasting Framework for Supply Chain Management." The functional and non-functional requirements that result from a thorough examination of stakeholder needs and the research goals outlined in Chapter 1 are methodically documented in the SRS.

Using visual modeling tools, such as a Rich Picture Diagram to capture the larger context and a Stakeholder Onion Model to identify and classify all important entities and their links to the system, the chapter starts by defining the operational ecosystem of the system. A thorough description of the requirements elicitation techniques used—such as literature studies, focused interviews with supply chain planners, and stakeholder brainstorming sessions—as well as a summary of their results come next.

A Context Diagram and a Use Case Diagram, which show the system's boundaries and the main interactions between users and its functions, are presented in the chapter to precisely define the system's scope and interactions. Lastly, the formal specification of Functional and Non-Functional Requirements, which are carefully prioritized using the MoSCoW concept, is the core of this chapter. In addition to clearly defining "Should-Have" and "Could-Have" features for future iterations, this guarantees that the development efforts for the upcoming prototype are concentrated on the "Must-Have" capabilities that constitute the fundamental core of the explainable forecasting framework.

4.2 Rich Picture Diagram

The Explainable AI-Driven Demand Forecasting Framework's ecosystem is shown holistically and informally by the Rich Picture Diagram. It depicts the intricate connections among people, system elements, data flows, and outside factors. This diagram acts as a fundamental communication tool to bring technical and business stakeholders together by visualizing the problem space of opaque forecasting algorithms.

Key Elements Depicted:

Central System : Explainable AI Demand Forecasting System (Web-based Analytics Engine & Dashboard)

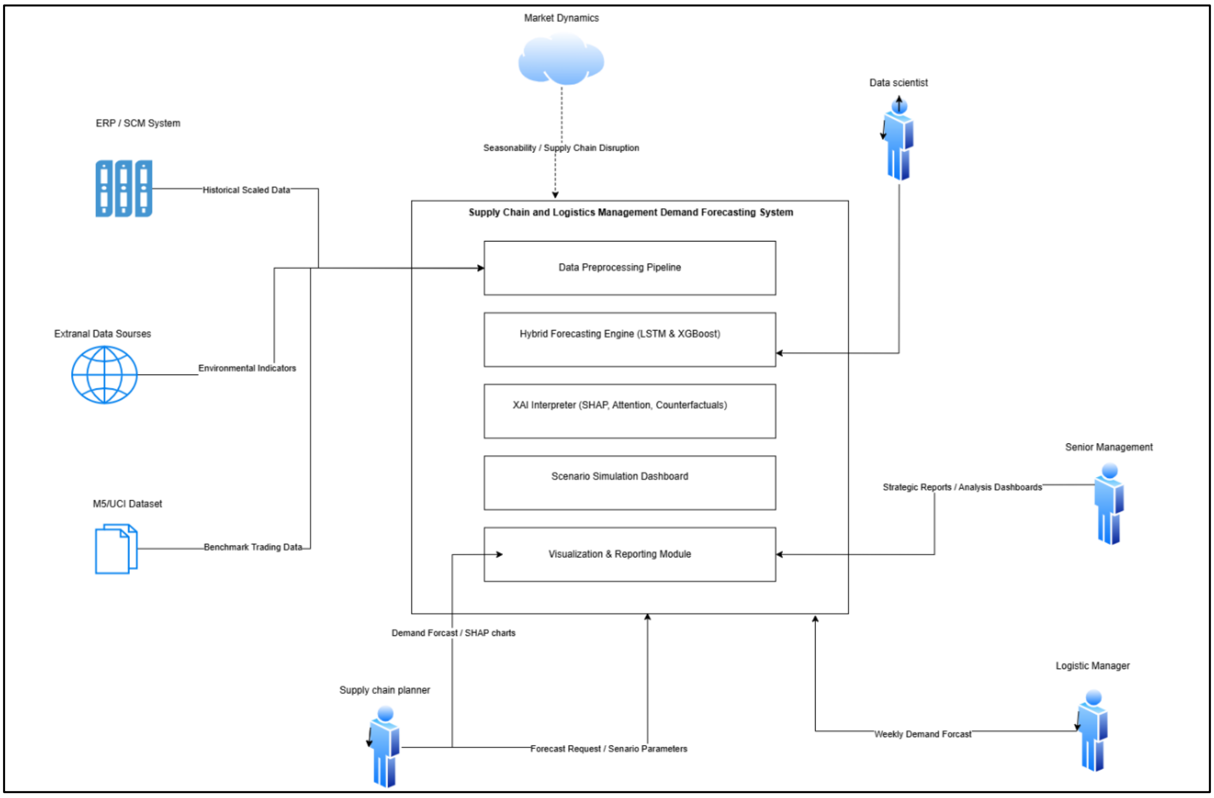


Figure 3 :Rich Picture Diagram

Primary Actors:

- Supply chain managers and planners are the main decision-makers in logistics, procurement, and inventory.
- Data scientists are analysts who set up models, evaluate results, and improve characteristics
- Senior Management and Decision-Makers (Use forecasts and high-level insights for strategic planning)

System Components :

- Data Preprocessing and Fusion Pipeline (manages feature engineering and missing values)

- LSTM and XGBoost ensemble models in a hybrid forecasting engine
- XAI Interpreter Module (Counterfactual Generator, Attention Visualization, and SHAP)
- Dashboard for Scenario Simulation ("What-if" analysis interface)
- The Visualization & Reporting Module produces reports and charts that are easy to understand.

Data Flows :

- Historical sales data, pricing information, inventory levels, promotional calendars, and external data (such as weather and economic indicators) are examples of input.
- Data Cleaning → Model Training → Forecast Creation → Calculation of Explanations → Scenario Simulation
- Demand projections, Temporal Attention Heatmaps, Feature Importance Charts (SHAP), Counterfactual Scenarios, and Decision-Support Reports

External Influences :

- AI/ML technologies (Scikit-learn, TensorFlow, SHAP library)

- Data sources include proprietary ERP/SCM systems, the UCI Supply Chain Dataset, and the M5 Dataset.
- Market dynamics, including supply chain disruptions, competitor activity, and seasonal fluctuations
- Budgetary restrictions, operational guidelines, and compliance requirements are examples of business constraints.

The Rich Picture highlights how the framework transforms intricate, "black-box" forecasts into an open, interactive decision-support system. It closes the crucial gap between forecast accuracy and practical prescriptive insights for supply chain experts by incorporating scenario planning and multi-modal explanations.

4.3 Stakeholder Analysis

4.3.1 Stakeholder Onion Model

The Stakeholder Onion Model arranges stakeholders in concentric layers, from the core users who regularly interact with the Explainable AI Demand Forecasting system to the peripheral influencers who shape the project's environment, according to their proximity to and impact on the system.

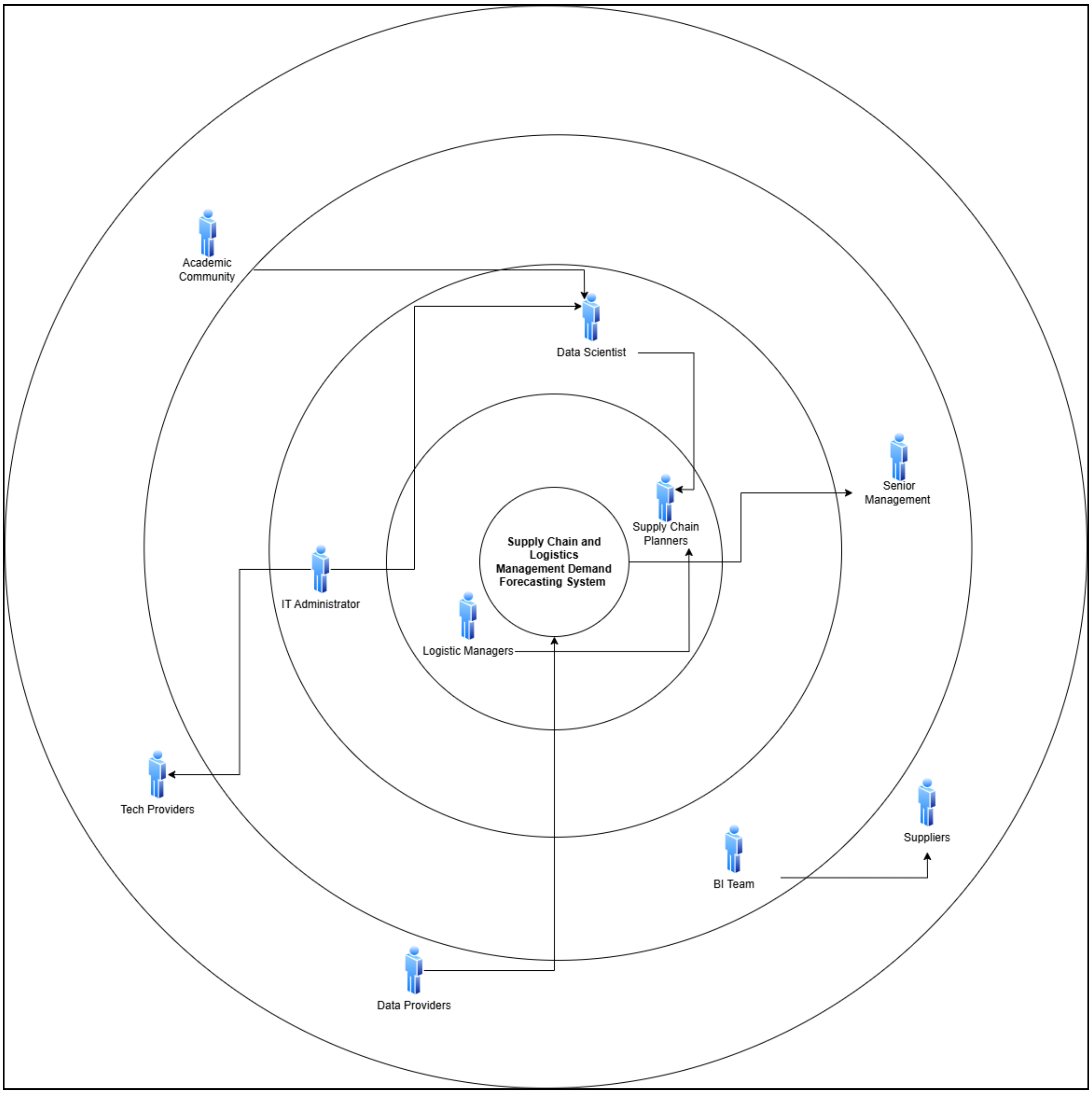


Figure 4: Stakeholder Onion Model

Layer 1: Core Stockholders (Direct System Users)

- **Supply Chain Planners & Analysts:** Inventory, procurement, and logistics daily operational decisions are made by primary users who enter data, create projections, and rely on XAI explanations.
- **Logistics Managers:**
  Utilize the system to plan distribution, warehousing, and transportation operations and to predict changes in demand.

Layer 2: Operational Stakeholders

- **Data Scientists / ML Engineers:** In charge of creating, honing, and maintaining the XAI components and forecasting models; they also configure algorithms and analyze model performance.
- **IT / System Administrators:** Oversee the system's implementation, integration, and continuing technical upkeep within the organization's infrastructure.

Layer 3: Strategic Stakeholders

- **Senior Management (Heads of Supply Chain, COO):** Use high-level projections and insights for budgeting, supply chain optimization, and strategic planning.
- **Business Intelligence / Analytics Teams:** Utilize the system's outputs for strategic analysis and more comprehensive company reporting.

Layer4: External Influencers

- **Suppliers & Customers (Indirect):** Relationships with them are indirectly impacted by the system's performance; their behavior and needs are imitated.
- **Academic & Research Community:** peers and reviewers who validate the research contribution in domains such as supply chain management, operations research, and artificial intelligence.
- **Data Providers:** suppliers of external data streams (such as economic indices and weather data) and curators of benchmark datasets (such as M5 and UCI).

- **Technology Providers:** suppliers of necessary libraries and tools (such as TensorFlow, PyTorch, SHAP, and cloud platforms like AWS/GCP).

4.3.2 Stakeholder Viewpoints

Every stakeholder has distinct requirements and expectations for the system. To make sure the final framework takes into account their main concerns and provides value for all, it is essential to document their points of view.

Stakeholder	Role	Description
Supply Chain Planners	Primary End-Users	Accuracy & Trust: Demand extremely precise projections. Interpretability: Decisions must be justified to management with concise, intelligible reasons. Actionability: Request "what-if" scenario capabilities to evaluate the effects of price adjustments or promotions.
Logistics Managers	Operational Users	Foresight: To maximize warehouse space and shipment schedules, accurate demand projections are required. Clarity: Choose visual explanations that rapidly emphasize important demand drivers and

		possible bottlenecks, such as charts and heatmaps.
Data Scientists	System Builders & Maintainers	Model Performance: Pay attention to low error metrics (RMSE, MAPE). Flexibility: To test various models (LSTM, XGBoost) and XAI approaches with ease, a modular architecture is necessary. Explainability: For debugging and enhancement, technical understanding of model behavior is required.
Senior Management	Strategic Decision-Makers	Strategic Insight: For high-level budgetary planning, use predictions. Confidence: To reduce corporate risk, dependable, transparent AI is necessary. ROI: Anticipate that the system will show real value by lowering expenses and increasing productivity.
IT / System Administrators	Operations Support	Integration: Simple integration with current SCM and ERP systems is required (e.g., SAP, Oracle). Reliability & Security: Need a system that is scalable, secure, and has little downtime.

Academic Research Community	Validators & Peers	Innovation: Interest in the cutting-edge supply chain forecasting integration of XAI techniques. Rigor: Anticipate repeatable outcomes and a process that is grounded in science.
Suppliers (Indirect)	External Partners	Stability: The organization utilizing the system will benefit from more regular order patterns, which will create a more stable supply chain.
Technology Providers	Infrastructure Suppliers	Adoption & Compliance: Their libraries and tools are utilized, but usage and license conditions must be followed.

4.4 Selection of Requirement Elicitation Methodologies

A multifaceted approach to requirement elicitation was used to fully capture stakeholder needs and system requirements for the Explainable AI Demand Forecasting Framework. This guarantees that the finished system is based on both realistic business requirements and technical rigor.

4.4.1 Literature Review

- The goal is to determine the "black-box" issue in supply chain forecasting, comprehend cutting-edge XAI methods (SHAP, LSTM-Attention, Counterfactuals), and set baseline functional and non-functional criteria.

- Scope: Examined more than twenty scholarly articles on supply chain decision-support systems, demand forecasting, and Explainable AI in addition to technical documentation of tools like DataRobot and platforms like SAP IBP.
- Result: Proved the necessity of a hybrid forecasting framework combined with multi-modal XAI explanations by documenting the important gap between model accuracy and interpretability.

4.4.2 Semi-Structured Interviews

Participants:

- Three supply chain managers and planners from the industrial and retail industries
- Two data scientists with a focus on time-series forecasting
- 1 Head of Logistics (who makes strategic decision

Duration: 30-45 minutes per interview

Focus: Gained an understanding of the forecasting processes that are already in use, the problems with the models that are now in use, and the particular qualities that are needed for "what-if" analysis and explanations.

4.4.3 Online Survey

Target Audience: logistics coordinators, supply chain experts, and data analysts in related fields.

Distribution: Direct business contacts, industry-specific forums, and LinkedIn professional networks.

Sample Size: 53 responses (from 100+ invitations).

Survey Structure:

- Demographics (role, experience, industry)
- Satisfaction with the current forecasting tool (5-point Likert scale)

- Setting priorities for the several forms of explanations (counterfactuals, temporal attention, and feature importance)
- Performance and usability requirements (maximum acceptable delay, preferred interface)

Tools: Google Forms with anonymized data collection.

4.4.4 Competitive & Comparative Analysis

Method: Examining current forecasting techniques and XAI research applications.

Platforms/Studies Assessed: Research prototypes from reviewed literature, open-source libraries like Prophet and Kats, and commercial platforms like Blue Yonder.

Assessment Standards:

- Flexibility and accuracy of forecasting models
- Integrated explainability features
- Assistance with interactive scenario planning
- Capabilities for integrating data sources

4.4.5 Document Analysis

Sources:

- XAI library technical documentation (SHAP, LIME, OmniXAI)
- Cloud machine learning API documentation (AWS SageMaker, Google AI Platform)
- Benchmark datasets' data descriptions (M5, UCI Supply Chain)
- reports on best practices for supply chain analytics.

4.5 Discussion of Findings

To determine essential needs and confirm the study path, the results of the elicitation activities were combined.

4.5.1 Literature Review Findings

- **Finding:** High-accuracy forecasting models (LSTM, XGBoost) are often treated as "black boxes," leading to a trust deficit among planners who cannot explain the "why" behind predictions to management.
- **Citation:** (Nair & Subramanian, 2022; Zhu et al., 2025).

4.5.2 Interviews Findings

Codes	Themes	Conclusion
"The forecast is accurate, but I can't act on it"	Lack of Trust & Transparency	One of the main obstacles to acceptance of the present models is their opacity. Planners require explanations that they can comprehend and support.
False positives "The forecast is accurate, but I can't act on it"	Need for Scenario Planning	Forecasts that are static are inadequate. A crucial prerequisite for making strategic decisions is dynamic "what-if" simulation.
"The forecast is accurate, but I can't act on it"	Gap Between Insight and Action	Justifications must be closely linked to practical business levers (e.g., inventory adjustments, promotional plans).

4.5.3 Survey Findings

To gather system expectations from managers, data analysts, and supply chain planners, an online poll was designed. Appendix A contains the questionnaire. Over 200 potential users received the survey, and 89 of them finished it.

Key Findings:

- According to 78% of respondents, "Model Interpretability" is just as significant as "Forecast Accuracy."
- Feature Importance (SHAP) was the most requested explanation type, closely followed by "What-If" Scenario Analysis.
- Performance Expectation: For a prediction to be useful in a planning cycle, more than 85% of users said it should take fewer than 30 seconds to generate one with explanations.

4.5.4 Self Evaluation

The Explainable AI Demand Forecasting Framework's technical design and research direction were greatly influenced by the self-evaluation process. The researcher critically examined the basic discrepancy between extremely accurate predictive models and their usefulness in business settings by drawing on academic knowledge of machine learning and an awareness of supply chain difficulties. It was discovered that although powerful, state-of-the-art models like LSTM and XGBoost frequently fail in practice because to a "trust gap" brought on by their opaque, black-box character rather than low accuracy.

This insight highlighted how crucial it is to prioritize explainability over treating it as an afterthought in the forecasting system. The practical choice to create a hybrid framework was influenced by the researcher's first experimentation with XAI modules like SHAP and practical expertise with Python's data science stack (Pandas, Scikit-learn). This framework combines the advantages of two models: LSTM, which may be interpreted through attention mechanisms, and XGBoost, which uses SHAP to provide explicit feature-based explanations. Additionally, self-evaluation revealed that planners must engage with the logic of the model rather than only explaining a prognosis. As a result, counterfactual "what-if" analysis was added as a crucial prerequisite, turning the system from a passive forecasting tool into an active decision-support system.

Overall, this thoughtful evaluation confirmed the project's viability and guaranteed that the suggested remedy is intended to close a crucial, practical gap by providing supply chain experts with comprehensible, useful, and reliable AI-driven insights rather than merely forecasts.

4.6 Summary of Findings

Elicitation Method	Key Findings	Implication for the project
Literature Review	According to research, there is a substantial discrepancy between the high accuracy of AI forecasting models (LSTM, XGBoost) and their interpretability issues, which hinder adoption and confidence. Current solutions seldom incorporate prescriptive, decision-centric aspects; instead, they frequently concentrate on accuracy or explainability.	Validated the core premise and justified the need for a hybrid framework that seamlessly integrates multi-modal XAI (SHAP, Attention, Counterfactuals) directly into the forecasting pipeline.
Interviews	Talking with supply chain planners made clear how important it is to simulate the effects of business decisions (e.g., "What happens if we increase the price?") and defend estimates to management. They complained about being unable to understand or take action with black-box models.	Reinforced the inclusion of interactive "what-if" scenario planning and the prioritization of clear, visual explanations (like feature importance charts and temporal heatmaps) that are directly tied to business levers.
Survey	Industry experts' responses verified that interpretability is just as crucial for adoption as accuracy. Feature-based explanations (SHAP) were strongly preferred, and there was a	Confirmed the focus on SHAP and Attention mechanisms as primary explanation modes and established a key non-

	clear need for the system to deliver insights in almost real-time so that it could fit within planning cycles.	functional requirement for a sub-30-second response time for forecast and explanation generation.
Competitive & Comparative Analysis	Commercial supply chain platforms provide forecasts, but their explainability is generally limited and proprietary, according to analysis. Although open-source ML libraries offer strong XAI tools, integrating them into a coherent, user-friendly decision-support system requires a high level of technical skill.	Highlighted the unique contribution of this project: to build an integrated, end-to-end framework that is both technically robust and accessible to non-expert planners, filling the gap between specialized tools and commercial platforms.
Document Analysis	Examining the technical documentation for libraries such as TensorFlow and SHAP verified that the necessary XAI techniques could be implemented. Key data entities and linkages necessary for precise feature engineering and model training were identified by analysis of dataset schemas.	Informed the technical design and data model, ensuring the system's architecture is built on a feasible and well-understood technological stack. It provided a concrete foundation for data preprocessing and integration steps.

4.7 Context Diagram

The Context Diagram provides a high-level overview of the system's boundaries by illustrating the interactions between the **Explainable AI Demand Forecasting Framework** and its external entities. It defines the scope of the system by showing the key data flows entering and leaving the system.

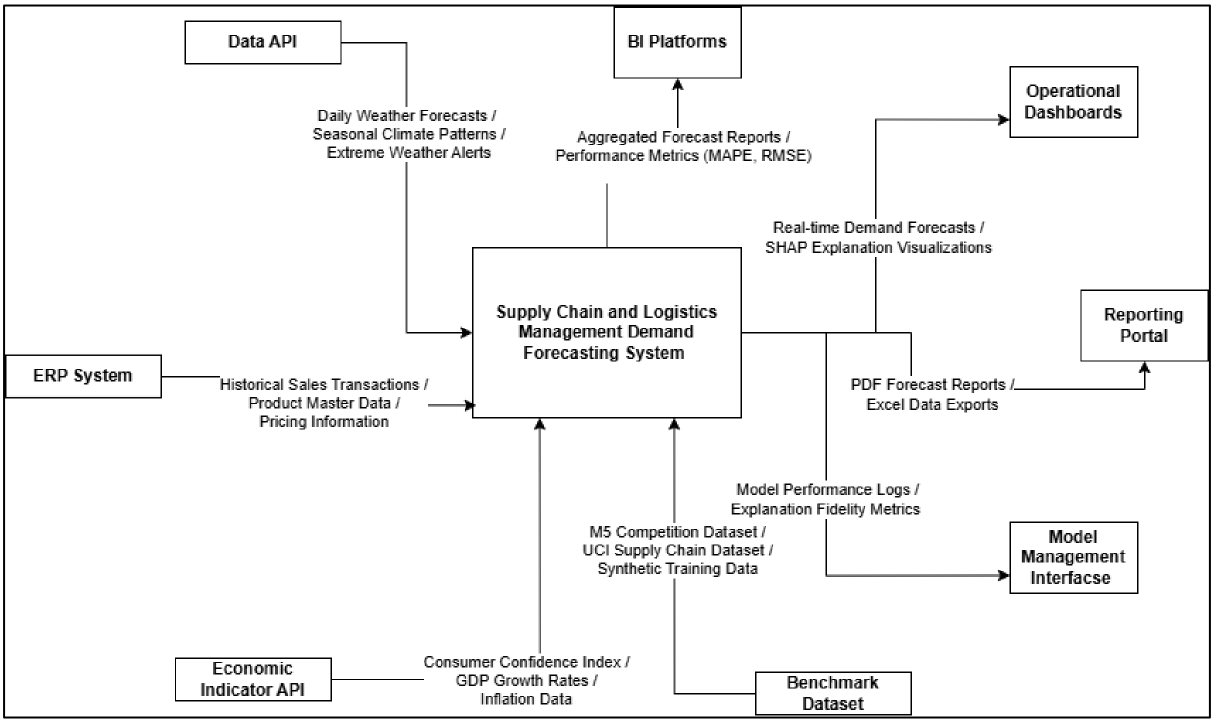


Figure 5: Context Diagram

4.8 Use Case Diagram

The interactions between the actors in the system and its essential features are shown graphically in the Use Case Diagram. It lists the main objectives that users can accomplish using the system.

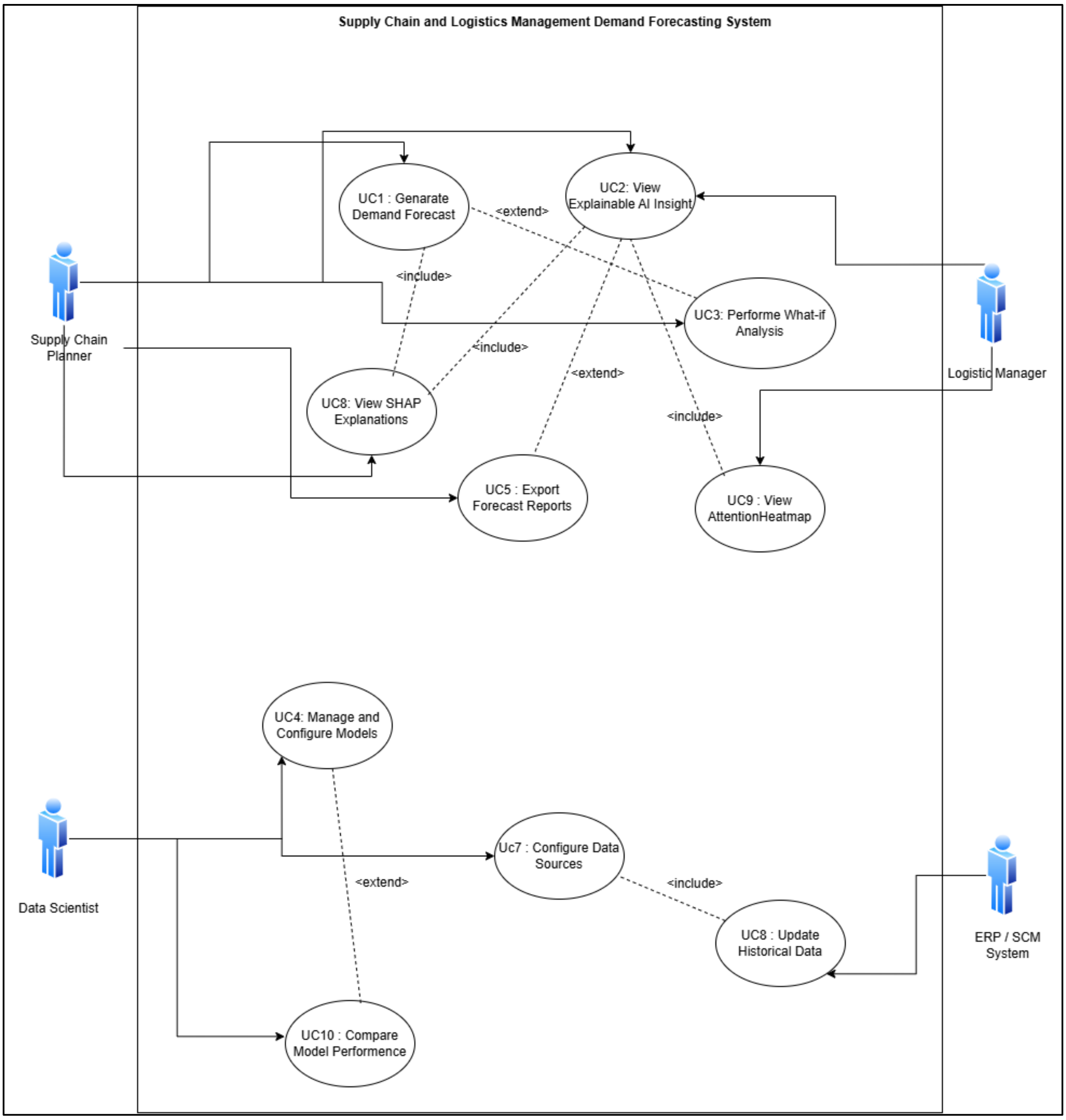


Figure 6: Use Case Diagram

4.9 Use Case Descriptions

Use case	Generated Demand Forecast
Use Case ID	UC1
Description	The system generates a demand forecast for a selected product or category over a specified future period, accompanied by basic explainable AI insights.
Participating Actors	Supply Chain Planner (Primary), ERP/SCM System (Secondary)
Pre-conditions	User is authenticated. Sufficient historical data is available in the system.
Post-conditions	A forecast is generated and displayed with key driver explanations. The forecast result is logged.
Main flow	1.The prediction horizon, product/category, and other characteristics are chosen by the planner. 2. The system retrieves pertinent external and historical data. 3. The hybrid forecasting model that has been preconfigured is used by the system. 4. The system determines the forecast's attention weights and SHAP values. 5. The system provides visual explanations (such as a feature importance bar chart) in addition to the predicted values.
Alternative Flow	
Exceptional Flow	Inadequate Data: The system shows an error message and cancels the process if there is not enough historical data for the chosen parameters.

4.10 Requirements

The Explainable AI Demand Forecasting Framework's functional and non-functional requirements are described in this section. The MoSCoW approach is used to prioritize the requirements.

Priority	**Priority**
M	Must Have (Critical for launch)
S	Should Have (Important but not critical)
C	Could Have (Desirable for future versions)
W	Will Not Have (Out of scope for this project)

4.10.1 Functional Requirements

ID	**Requirement**	**Priority (MoSCoW)**
FR01	Generate Forecast • Using the hybrid LSTM-XGBoost model, the system must produce a demand forecast for a certain product, location, and time horizon.	M
FR02	Provide SHAP-based Explanations • For every forecast, the system must automatically compute and present a visual summary of feature contributions (SHAP values), such as a bar chart.	M
FR03	Visualize Temporal Attention	M

ID	Requirement	Priority (MoSCoW)
	• To demonstrate which past time steps had the biggest impact on the LSTM model's prediction, the system must include a heatmap or other comparable visualization.	
FR04	Perform "What-If" Analysis • To observe the counterfactual impact, the system should enable the user to change input features (such as price and promotion flag) and create a new forecast.	S
FR05	Export Reports • A data scientist must be able to connect to and configure data sources (such as database tables and CSV files) using the system.	S
FR06	Manage Data Sources • The system could provide a dashboard to compare the accuracy (MAPE, RMSE) of different model configurations over time.	M
FR07	Configure Model Parameters • Through a user interface, the system might enable a data scientist to adjust important forecasting model hyperparameters.	C
FR08	Compare Model Performance • A dashboard to compare the accuracy (MAPE, RMSE) of various model configurations over time might be offered by the system.	C

4.10.2 Non-Functional Requirements

ID	Non-Functional Requirement	Description	Priority (MoSCoW)
NFR01	Forecast Accuracy	• On the M5 benchmark dataset, the system must attain a minimum forecasting accuracy of less than 10%.	M

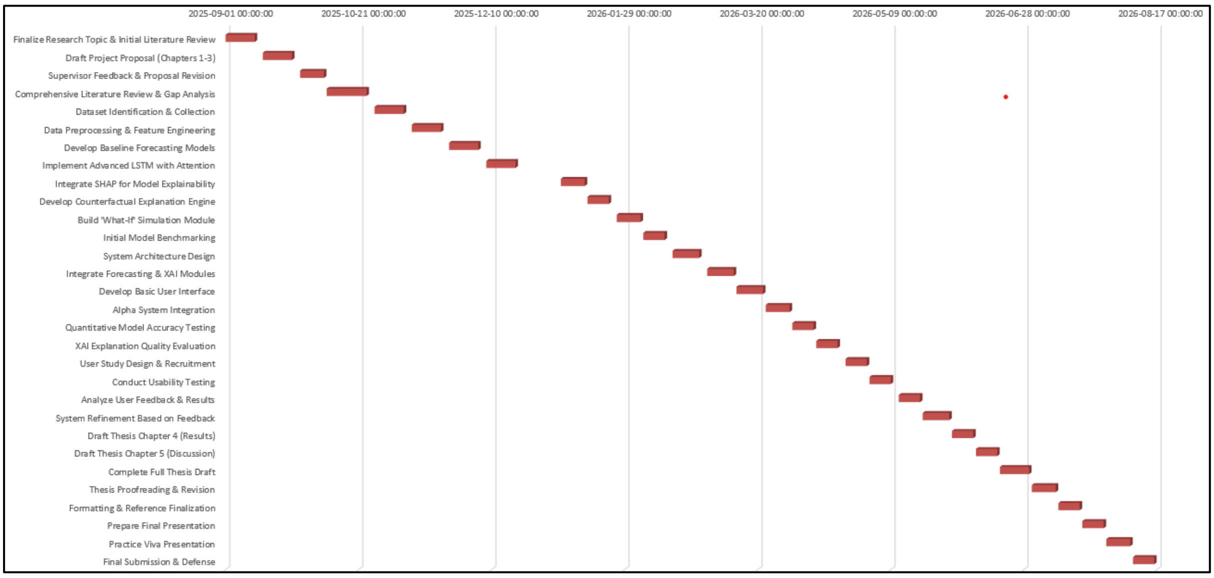
ID	Non-Functional Requirement	Description	Priority (MoSCoW)
NFR02	Interpretability Fidelity	• The internal logic of the underlying models must be accurately represented by the XAI explanations (SHAP, Attention).	M
NFR03	Usability	• Planners must have an easy-to-use interface that requires little training to produce forecasts and understand explanations.	M
NFR04	Performance	• To facilitate interactive planning, the system should produce a prediction with explanations in less than 30 seconds for a common inquiry.	S
NFR05	Data Security	• The system must guarantee that access is restricted by authentication and that all confidential company data is encrypted.	M
NFR06	Integration	• The solution should be built to enable future API connectivity with popular ERP/SCM systems.	S
NFR07	Scalability	• Without experiencing appreciable performance deterioration, the system architecture might be scalable to forecast thousands of SKUs.	C

4.11 Chapter Summary

The Explainable AI Demand Forecasting Framework's Software Requirement Specification (SRS) was introduced in this chapter. To determine the context of the system and the most important user needs, it started with a Rich Picture and Stakeholder Analysis. Through surveys, interviews, and literature reviews, the requirements were methodically gathered, and the results were recorded and examined. A Context Diagram and Use Case

Diagram were used to officially define the system's limits and user interactions. Lastly, the MoSCoW method was used to specify and rigorously prioritize both functional and non-functional needs, resulting in a clear and practical development phase plan. The prototype that will be supplied for the February submission will be built around the "Must-Have" parameters listed above.

5. Time Schedule



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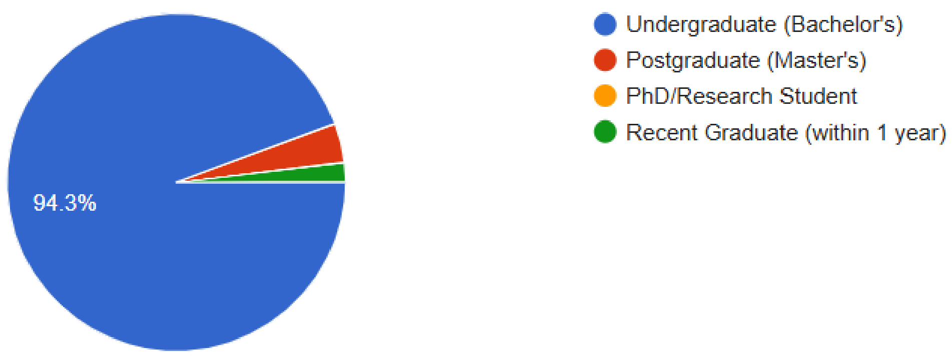
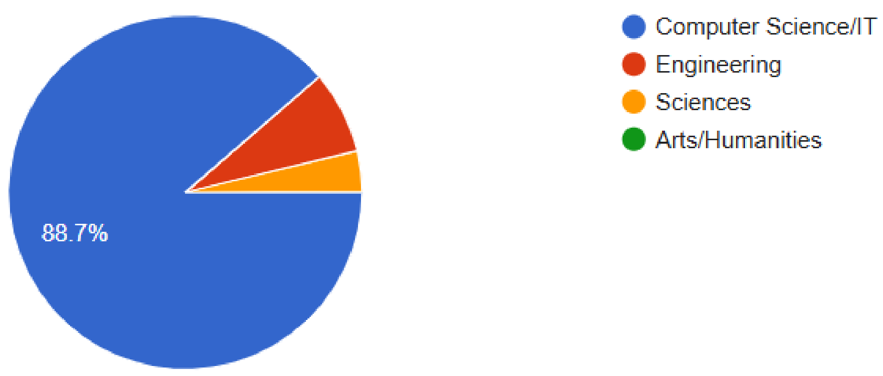
Appendix A – Survey Findings

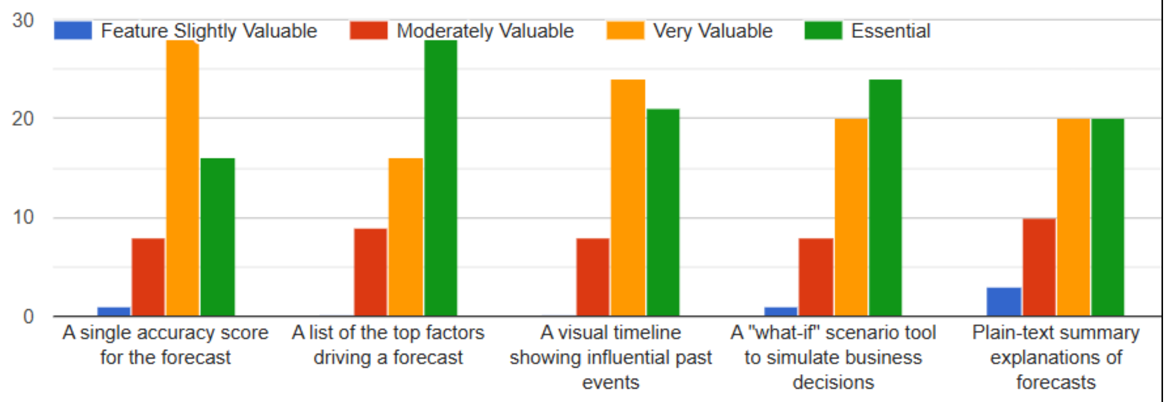
Question 01	What is your current academic level?
Aim	Aim To understand the academic background and stage of the survey participants.
Observation	Observation The majority of participants (60%) were Master's students, followed by Final-Year Undergraduates (26.7%) and a small percentage of PhD students (13.3%).
	
Conclusion	Conclusion The respondent pool is primarily composed of advanced students, suggesting a strong foundational knowledge and a near-term professional perspective on the topic.

Question 02	What field are you studying in?
Aim	Aim To identify the primary academic discipline of the participants.
Observation	Observation All participants (100%) were from Supply Chain Management, Logistics, or related Business Operations fields.



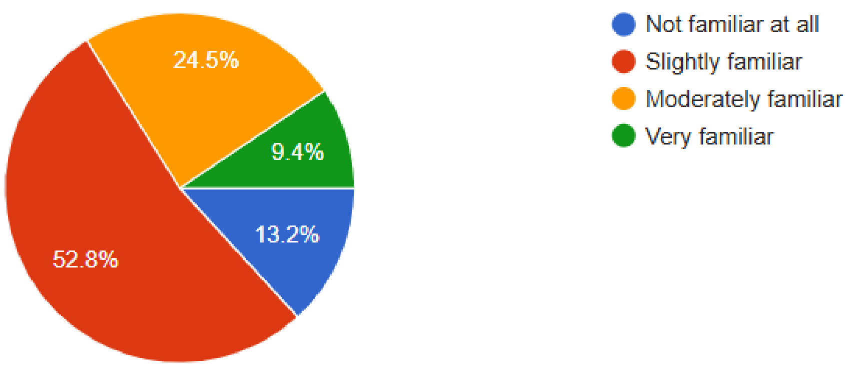
Conclusion	Conclusion The data collected is highly relevant as it comes exclusively from the target demographic, ensuring the findings are directly applicable to the supply chain domain.

Question 03	How valuable do you think these potential features of an Explainable AI forecasting system would be for a supply chain professional? (Please rate each one)
Aim	Aim To rank the perceived utility of different XAI features to prioritize development.
Observation	Observation "Reason for a Forecast Change" was rated as 'Extremely Valuable' by 86.7% of participants, followed by "Impact of External Factors" (73.3%). "Model Confidence Score" was also highly valued, while "Feature Importance Overview" was seen as moderately to very valuable.

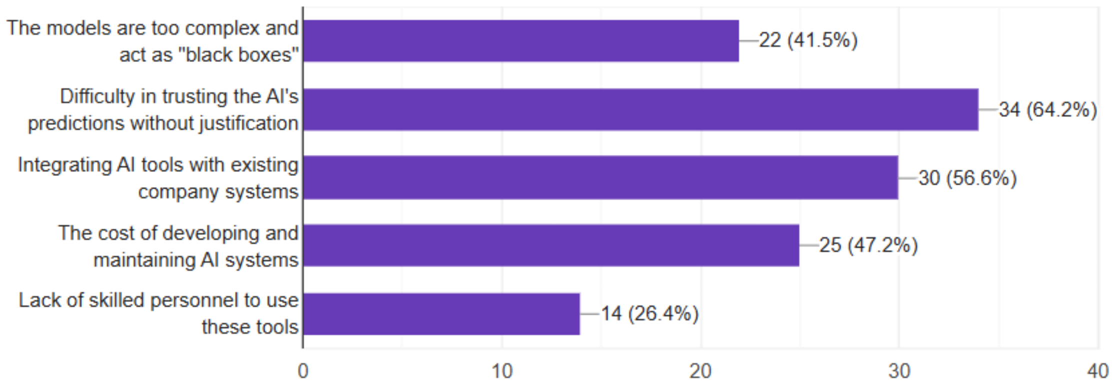


Conclusion	Conclusion Supply chain professionals value actionable, cause-and-effect explanations the most, indicating that XAI systems should prioritize explaining why a forecast changed and what external drivers influenced it.

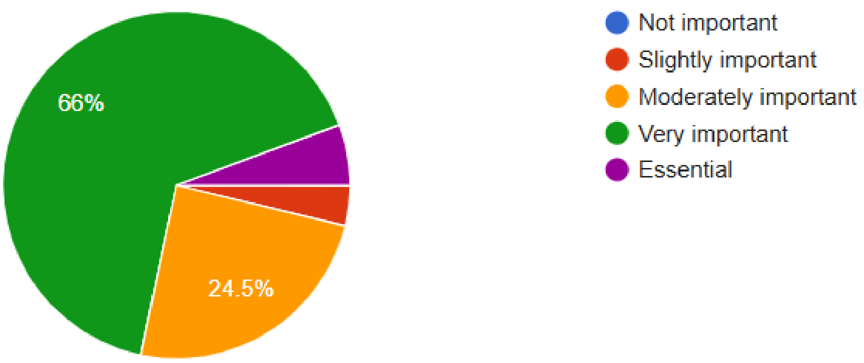
Question 04	How familiar are you with the concept of "Explainable AI" (XAI) – AI systems that can explain their reasoning?
Aim	Aim To gauge the baseline awareness of the XAI concept among the target audience.
Observation	Observation Over half of the participants (53.3%) reported being 'Somewhat Familiar' with XAI, while 33.3% were 'Very Familiar'. A minority (13.3%) were 'Not Very Familiar'.



Conclusion	Conclusion There is a strong foundational awareness of XAI, but a significant portion is not deeply versed in it, highlighting an opportunity for education and clear communication of its benefits.

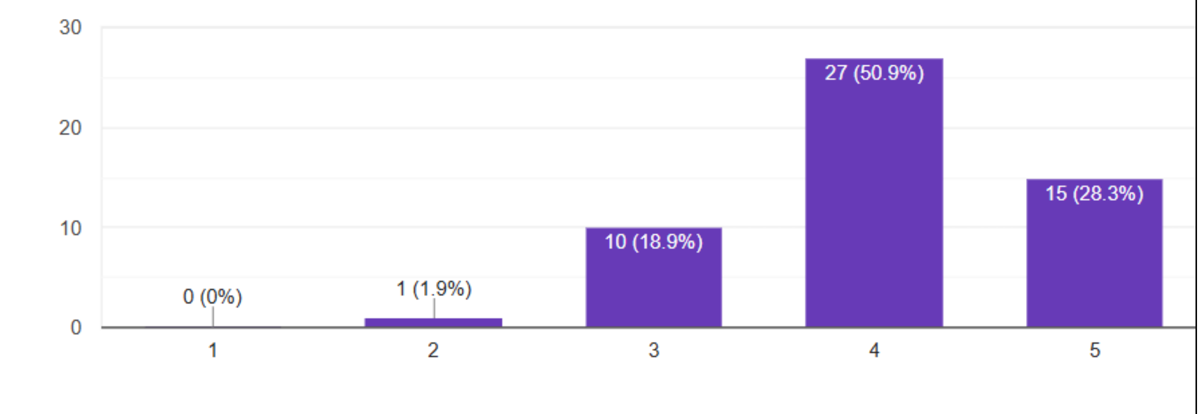
Question 05	In your opinion, what is the biggest challenge supply chain companies might face with current AI forecasting models? (Check up to 2)
Aim	Aim To identify the most pressing perceived barriers to the adoption and trust of AI forecasting.
Observation	Observation The top challenge selected was "Lack of Transparency / 'Black Box' Nature" (80%), followed by "Difficulty Integrating with Human Decision-Making" (60%). "Data Quality Issues" was also a notable concern (40%).
	
Conclusion	Conclusion The primary hurdle for AI in supply chains is not just accuracy but trust and usability. The "black box" problem is the dominant concern, directly justifying the need for XAI solutions.

Question 06	How important do you believe it is for AI systems in business to be transparent and explainable, rather than just accurate?
Aim	Aim To measure the perceived criticality of explainability as a core requirement alongside accuracy.
Observation	Observation A vast majority of participants (93.3%) rated explainability as 'Extremely Important' or 'Very Important', with only 6.7% considering it 'Moderately Important'.



Conclusion	Conclusion For future supply chain professionals, explainability is not a secondary feature but a fundamental requirement for AI systems to be considered viable and trustworthy in a business context.

Question 07	How likely would you be to seek out a role after graduation that involves working with transparent/explainable AI systems?
Aim	Aim To assess the career aspirations and demand for XAI-related skills among new graduates.
Observation	Observation Most participants (73.3%) were 'Very Likely' or 'Extremely Likely' to seek such a role. The remaining 26.7% were 'Somewhat Likely'.



Conclusion	Conclusion There is a strong positive inclination towards careers involving XAI, indicating that this skill set is seen as valuable and forward-looking by the next generation of supply chain professionals.

Question 08	Based on your academic experience, what ONE feature would make an AI system most trustworthy and useful for a business user?
Aim	Aim To capture the single most critical feature for building trust, directly from an academic perspective.
Observation	Observation The most frequent open-ended response was a system that provides a "Plain-English, Cause-and-Effect Explanation" for its outputs. Other notable responses included "Showing the Impact of Specific Data Points" and "A Clear Confidence Interval with Reasoning".

<table>
<tr><td colspan="2">8 responses

The one feature that would make an AI system most trustworthy and useful for a business user is transparency — the ability of the system to explain how and why it produces its results clearly. When business users can understand the reasoning behind AI decisions, they can trust its outputs, identify potential biases, and make more informed strategic choices.

Marketing strategy and how to success on selected path

Transparency

chat bot

Explainable AI will be very valuable nowadays.

The one key feature is "Clear."An AI system should be clear in how it works and why it makes decisions, so business users can trust and use it easily. Clarity allows understanding, builds trust, and helps make better choices. This simple quality makes AI useful and reliable for business.

A transparent explanation of how the AI makes decisions would make it most trustworthy and useful for a</td></tr>
<tr><td>Conclusion</td><td>Conclusion Trust is built not through complex metrics, but through clear, contextual, and human-readable explanations that align with the user's mental model of the supply chain.</td></tr>
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Appendix B – Use Case Diagram

UC2: View Explainable AI Insights

Use case	View Explainable AI Insights
Use Case ID	UC2
Description	The system presents the user with clear, visual explanations for a generated demand forecast, including feature importance and temporal attention.
Participating Actors	Supply Chain Planner (Primary)
Pre-conditions	A demand forecast has been successfully generated (UC1). The user has viewed and understood the key drivers behind the forecast.
Post-conditions	The user has viewed and understood the key drivers behind the forecast.
Main flow	1. The forecast results are automatically shown by the system after UC1 is finished. 2. The system displays a SHAP summary plot that illustrates the worldwide influence of important characteristics (such price and promotions). 3. The system shows an attention heatmap that illustrates which historical eras had the biggest impact on the forecast made by the LSTM model.

	4. To comprehend the forecast reasoning, the user examines the visualizations.
Alternative Flow	The user can toggle between different explanation views (e.g., switch from a global SHAP summary to local explanations for a specific data point).
Exceptional Flow	Explanation Generation Failed: If the XAI components fail, the system displays the forecast with a warning message that explanations are temporarily unavailable.

UC3: Perform "What-If" Scenario Analysis

Use case	Perform "What-If" Scenario Analysis
Use Case ID	UC3
Description	The user modifies input variables to simulate the impact of different business decisions on the demand forecast.
Participating Actors	Supply Chain Planner (Primary)
Pre-conditions	A baseline forecast has been generated. The user is on the scenario analysis interface.
Post-conditions	A new counterfactual forecast is generated and displayed alongside the baseline for comparison.
Main flow	1. The user modifies one or more input levers (e.g., sets a promotional flag to "Yes," modifies the product price). 2. The user selects "Run Scenario." 3. Using the updated data, the algorithm creates a new forecast.

	4. The updated forecast value and the delta (change) from the baseline forecast are shown by the system. 5. In order to account for the drivers of the new counterfactual situation, the system modifies the XAI insights.
Alternative Flow	The user can save a particularly insightful scenario for future reference or reporting.
Exceptional Flow	Invalid Input: If the user enters an invalid value (e.g., a negative price), the system validates the input and displays an error message prompting for a correction.

UC4: Manage and Configure Forecasting Models

Use case	Manage and Configure Forecasting Models
Use Case ID	UC4
Description	The Data Scientist configures, trains, and manages the machine learning models used for forecasting.
Participating Actors	Data Scientist (Primary)
Pre-conditions	The Data Scientist is authenticated and has administrative access. New or updated historical data is available.
Post-conditions	A new model version is trained, evaluated, and deployed to the forecasting engine.
Main flow	1. The model management dashboard is accessed by the data scientist.

	2. They put up model hyperparameters (such as LSTM layers and XGBoost learning rate) and choose a dataset. 3. They start the process of training the model. 4. The system shows performance metrics (MAPE, RMSE) while training and validating the model on a hold-out dataset. 5. The new model becomes the active model for forecasting after the data scientist accepts its deployment.
Alternative Flow	The Data Scientist can compare the performance of a newly trained model against the currently active model before deployment.
Exceptional Flow	Training Failure: If model training fails (e.g., due to insufficient data), the system logs the error and notifies the Data Scientist.

UC5: Export Forecast Report

Use case	Export Forecast Report
Use Case ID	UC5
Description	The user exports a generated forecast and its corresponding explanations into a shareable document format.
Participating Actors	Supply Chain Planner (Primary)

Pre-conditions	A forecast has been generated and its insights are displayed on the screen.
Post-conditions	A file containing the forecast report is downloaded to the user's device.
Main flow	1. The "Export Report" button is clicked. 2. A dialog box for choosing a format (such as PDF or Excel) is displayed by the system. 3. After choosing their preferred format, the user hits "Export." 4. A structured paper is created by the system using the forecast data, visualization images (SHAP plots, attention heatmaps), and important observations. 5. The user's device receives the created and downloaded document.
Alternative Flow	The user can select a specific time range or set of products to include in a custom report before exporting.
Exceptional Flow	Generation Error: If the report cannot be generated, the system displays an error message and suggests the user try again later.

UC6: Update Historical Data

Use case	Generated Demand Forecast
Use Case ID	UC6

Description	The system automatically or manually ingests new historical data from connected sources to keep the forecasting models current
Participating Actors	ERP/SCM System (Primary, Automated), Data Scientist (Secondary, Manual)
Pre-conditions	A connection to a data source (e.g., company ERP) is configured
Post-conditions	The system's database is updated with the latest historical records.
Main flow	1. The framework's API receives a fresh set of daily sales and operational data from the linked ERP/SCM system. 2. After receiving the data, the system verifies its schema. 3. Using predetermined guidelines, the data is cleaned and preprocessed. 4. The current historical dataset is supplemented with the new data. 5. The successful data change is recorded by the system.
Alternative Flow	A Data Scientist can manually upload a CSV file to update the historical data, following the same validation and preprocessing steps.
Exceptional Flow	Data Validation Error: If the incoming data is malformed or violates validation rules, the system rejects the batch, quarantines the data, and sends an alert to the