REPUBLIC OF TÜRKİYE

GRADUATE SCHOOL OF

ISTANBUL AREL UNIVERSITY

EXECUTIVE MASTER OF BUSINESS ADMINISTRATION

THE ROLE OF ARTIFICIAL INTELLIGENCE IN FORECASTING AND DEMAND PLANNING IN SUPPLY CHAIN IN FOOD INDUSTRIES

MASTER'S THESIS

SALMAN ALAM KHAN

İSTANBUL, 2025

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ACCEPTANCE AND APPROVAL

The Jury finds that "**THE ROLE OF ARTIFICIAL INTELLIGENCE IN FORECASTING AND DEMAND PLANNING IN SUPPLY CHAIN IN FOOD INDUSTRIES**" submitted by **SALMAN ALAM KHAN** on 11.04.2025, successfully passed the defense examination in partial fulfillment of the requirements of the Graduate School of Istanbul Arel University for the degree of Master's Thesis in Executive Master of Business Administration.

Jury Members	Signature
Supervisor Assoc. Prof. Dr Aylin Erdoğdu	………………………………………..
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It was approaved on ……………. with decision no. ……………. by Istanbul Arel University, Graduate School Executive Board.

………………………………………….

PROF. DR. ALİ AKDEMİR

Director of Graduate School

OATH STATEMENT

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

22.04.2025

SALMAN ALAM KHAN

ABSTRACT

THE ROLE OF ARTIFICIAL INTELLIGENCE IN FORECASTING AND DEMAND PLANNING IN SUPPLY CHAIN IN FOOD INDUSTRIES
MASTER'S THESİS

SALMAN ALAM KHAN
GRADUATE SCHOOL, ISTANBUL AREL UNIVERSITY
EXECUTIVE MASTER OF BUSINESS ADMINISTRATION
(SUPERVISOR: ASSOC. PROF. DR. AYLİN ERDOĞDU)

İSTANBUL, 2025

Artificial intelligence (AI) is transforming the food supply chain by enhancing forecasting and demand planning, offering advanced tools such as predictive analytics and machine learning to improve accuracy and responsiveness. This study explores the role of AI in addressing challenges within the food industry's supply chain, focusing on its impact on operational efficiency, forecasting accuracy, and the ability to meet fluctuating consumer demands. While AI technologies provide substantial benefits, issues such as data quality, integration with existing systems, and high implementation costs remain critical barriers. This research investigates how businesses adopt and utilize AI-driven solutions, examining the factors that influence their success and the extent to which these technologies optimize supply chain processes. The study aims to provide actionable insights for organizations, professionals, and policymakers to leverage AI strategically, enhancing competitive advantage and supply chain resilience. By identifying the drivers and challenges of AI adoption, the findings will support better decision-making in the integration of AI into supply chain management. The data collection involves surveys with approximately 370 professionals from the food industry, capturing their experiences with AI technologies, perceived benefits, and implementation challenges. The study seeks to guide food industry stakeholders in optimizing their supply chain operations through the effective use of AI technologies.

Key Words: Artificial Intelligence, Supply Chain, Food Industry, Forecasting, Demand Planning, Predictive Analytics, Efficiency.

ÖZET

GIDA SEKTÖRÜNDE TEDARİK ZİNCİRİ TAHMİNİ VE TALEP PLANLAMASINDA YAPAY ZEKA'NIN ROLÜ

YÜKSEK LİSANS TEZİ

SALMAN ALAM KHAN

İSTANBUL AREL ÜNİVERSİTESİ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

YÖNETİCİLER İÇİN İNGİLİZCE İŞLETME

(DANIŞMAN: PROF. DR. AYLİN ERDOĞDU)

İSTANBUL, 2025

Yapay zeka (AI), tahmin ve talep planlamasını geliştirerek gıda tedarik zincirini dönüştürüyor, doğruluk ve yanıt verme hızını artırmak için tahmine dayalı analitik ve makine öğrenimi gibi gelişmiş araçlar sunuyor. Bu çalışma, operasyonel verimlilik, tahmin doğruluğu ve değişken tüketici taleplerini karşılama yeteneği üzerindeki etkisine odaklanarak yapay zekanın gıda endüstrisinin tedarik zincirindeki zorlukları ele almadaki rolünü araştırıyor. Yapay zeka teknolojileri önemli faydalar sağlarken veri kalitesi, mevcut sistemlerle entegrasyon ve yüksek uygulama maliyetleri gibi konular kritik engeller olmaya devam ediyor. Bu araştırma, işletmelerin yapay zeka odaklı çözümleri nasıl benimsediğini ve kullandığını araştırıyor, başarılarını etkileyen faktörleri ve bu teknolojilerin tedarik zinciri süreçlerini ne ölçüde optimize ettiğini inceliyor. Çalışma, kuruluşlara, profesyonellere ve politika yapıcılara yapay zekayı stratejik olarak kullanma, rekabet avantajını ve tedarik zinciri esnekliğini artırma konusunda eyleme dönüştürülebilir bilgiler sağlamayı amaçlıyor. Yapay zekanın benimsenmesinin itici güçlerini ve zorluklarını belirleyerek bulgular, yapay zekanın tedarik zinciri yönetimine entegrasyonunda daha iyi karar almayı destekleyecektir. Veri toplama, gıda endüstrisinden yaklaşık 370 profesyonelle yapılan, onların yapay zeka teknolojileriyle ilgili deneyimlerini, algılanan faydalarını ve uygulama zorluklarını içeren anketleri içeriyor.Çalışma, gıda endüstrisi paydaşlarına yapay zeka teknolojilerinin etkin kullanımı yoluyla tedarik zinciri operasyonlarını optimize etme konusunda rehberlik etmeyi amaçlıyor.

Anahtar Kelimeler: Yapay Zeka, Tedarik Zinciri, Gıda Endüstrisi, Tahmin, Talep Planlama, Tahmine Dayalı Analitik, Verimlilik.

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PREFACE

This thesis can be described as a culmination of dedicated research and intellectual pursuit. The journey to its completion has been one of both scholarly diligence and personal growth, during which I was met with certain challenges and revelations that have profoundly shaped my understanding.

This work stands as a tribute to the guidance and mentorship of my advisor, Dr. Aylin Erdoğdu, who assisted me fully in every step and whose expertise and insight made the journey easier. I extend my gratitude to my family and friends back home, whose unwavering encouragement sustained me throughout this endeavor. Their belief in my abilities and the significance of my research served as a constant source of motivation. And last but not the least, I am highly grateful to God, for giving me the strength and capability to complete this work, in the face of adjusting to living in a completely foreign land.

22.04.2025

SALMAN ALAM KHAN

1 INTRODUCTION

1.1 Background of Supply Chain In Food Industries

Supply Chain Management (SCM) is a multi-faceted process used in the food industry to navigate the complex operations of getting food to the final consumer In many other industries food supply makes it especially challenging, because food perishes and food safety is of utmost importance (Johnston, 2019) There is a need to adhere to strict quality control procedures throughout the supply chain (Smith et al., 2020). SCM in the food industry from farm to pan must be well planned to ensure quality while maintaining quality and safety standards (Gupta & Sharma, 2018). In addition, the food supply chain must be flexible and sensitive to changes in the market due to factors such as seasons and changes in demand. Using a cold chain is also key, and many foods need a temperature-controlled environment to stay fresh. Traceability and transparency are becoming increasingly important, with consumers demanding knowledge of the origin and transport of their food. Furthermore, sustainable development and ethical outcomes emerge as important considerations, driving improvements in waste reduction, environmental design, and enforcement of appropriate business practices Technology adoption accelerates SCM transformation in the food industry, better forecasting, inventory management, supply chain partners and enables interoperability between them In this case a in this dynamic context, it is imperative that the SCM is effective to meet customer expectations for food safety, and sustainable sourcing , and, in order to increase efficiency and control risks attached.

1.2 Significance of Forecasting and Demand Planning

Forecasting and demand planning play an important role in the efficient functioning of supply chains, particularly in the food industry. These techniques are key pillars of strategic decisions, aid allocation, and operational efficiencies among delivery chains By appropriately forecasting destiny wishes, corporations can provide inventory, planning production tactics, and delivery techniques have progressed, thereby lowering prices and increasing client satisfaction. As the availability of perishable goods fluctuates, transportation delays, unexpected shifts in customer preferences, and the importance of minimizing spoilage and time-sensitive decisions necessitate the ability to anticipate and respond to demand variability. This ensures availability, reduces waste, enhances efficiency, and promotes flexibility in response to dynamic market conditions. The importance of forecasting and demand control cannot be overstated, as they are essential components for improving supply chain performance, mitigating risks, and meeting the evolving needs and expectations of customers. Forecasting plays a role, in managing stocks helping businesses maintain a balance between supply and demand. By analysing data, market trends and using analytics food manufacturers can determine the right inventory levels to avoid issues like overstocking or running out of stock. This strategy not cuts down on storage costs. Also reduces waste ensuring that products are consistently available to meet customer needs.

Additionally having demand planning strategies is crucial for optimizing production schedules and procurement processes. By aligning production with anticipated demands food companies can streamline their operations reduce capacity and lower expenses related to overtime labour or rushed sourcing of ingredients due to last minute requirements, for deliveries.

Customer satisfaction is also the central focus of effective forecasting and demand planning in the food industry. It is crucial to have products readily available to build trust and loyalty among consumers which will increase the market share of the company in industry. Accurate forecasting ensures that the right products are stocked on shelves at the right times, minimizing the risk of stockouts and improving the overall customer experience, which will lead to increase company’s overall efficiency and productivity.

1.3 Emergence of Artificial Intelligence in Supply Chain Management

The last few years have seen the incorporation of Artificial Intelligence (AI) into different fields, causing a massive transformation in conventional methods globally. AI involves machines simulating human intelligence processes and covers several applications from natural language processing to computer vision. Due to its versatility and adaptability, it has generated widespread interest across an array of domains with the food industry benefiting notably from such transformative capacities.

The food supply chain network depends on proper forecasting and demand planning to maintain efficiency, cost-effectiveness, and customer satisfaction. However, traditional methods often struggle with the constantly changing demands of consumers, market trends and intricate logistics. With AI technology becoming prevalent in this field it has made a significant impact by providing opportunities for optimization processes while mitigating risks so strategic decision-making is possible like never before.

1.4 Research Question

How does the utilization of artificial intelligence (AI) technologies impact the accuracy of forecasting and demand planning in the food supply chain?

How does the implementation of AI-driven predictive analytics tools influence supply chain responsiveness in meeting fluctuating consumer demand in the food industry?

1.5 Hypothesis

1.5.1 Hypothesis 1 (H0)

"There is no significant relationship between the utilization of AI technologies and the accuracy of forecasting and demand planning in the food supply chain."

1.5.2 **Hypothesis** 2 (H1)

"There is a significant relationship between the utilization of AI technologies and the accuracy of forecasting and demand planning in the food supply chain."

Dependent Variable: Accuracy of forecasting and demand planning.

Independent Variable: Utilization of AI technologies.

1.5.3 Hypothesis 3 (H0)

“The implementation of AI-driven predictive analytics tools does not have a significant influence on supply chain responsiveness in meeting fluctuating consumer demand in the food industry.”

1.5.4 Hypothesis 4 (H1)

“The implementation of AI-driven predictive analytics tools has a significant positive influence on supply chain responsiveness in meeting fluctuating consumer demand in the food industry.”

Dependent Variable: Supply chain responsiveness.

Independent Variable: Implementation of AI-driven predictive analytics tools.

1.6 Significance of Study

In the realm of supply chain management, this thesis examines how Artificial Intelligence impacts forecasting and demand planning in the food industry. It analyzes AI's underlying principles, methodologies, challenges, and implementations to provide a comprehensive understanding of its role in reshaping future dynamics within food-related sectors' supply chains.

This study aims to explore the nuances of AI-powered forecasting and demand planning, utilizing a combination of theoretical examination and applied examples. The potential benefits in terms of enhancing supply chain efficiency, precision, and flexibility will be highlighted through an analysis that demonstrates how AI can transform operations. Ultimately contributing to discussions about leveraging technological progressions for managing modern-day supply chains with particular emphasis on food industry evolution.
The multifaceted role of Artificial Intelligence in forecasting and demand planning within the food industry's supply chain. By examining AI-driven forecasting and demand planning intricacies, challenges, as well as real-world applications, this

research endeavours to highlight its transformative potential and implications for future food sector supply chain management.

1.7 Aims and Objectives Of Study:

1. Evaluate the influence of AI utilization on the accuracy of forecasting and demand planning in the food supply chain.

Investigate how the implementation of AI-driven predictive analytics tools affects supply chain responsiveness in addressing fluctuating consumer demand within the food industry.

2 LITERATURE REVIEW

2.1 Historical Evolution of SCM

Supply Chain Management (SCM) has evolved significantly over the years, shaped by key milestones, technological advancements, and paradigm shifts. Initially, SCM was primarily focused on optimizing individual functions within organizations, such as inventory management and procurement. However, the concept of SCM as we know it today began to take shape in the 1980s and 1990s with the emergence of integrated supply chain systems (Mentzer et al., 2001).

One of the earliest milestones in SCM was the introduction of Material Requirements Planning (MRP) systems in the 1960s, which enabled manufacturers to better plan and manage their production processes (Forrester, 1958). This was followed by the development of Enterprise Resource Planning (ERP) systems in the 1990s, which integrated various business functions including production, finance, and logistics into a single cohesive system (Davenport, 1998).

The 21st century saw the rise of globalization and the increasing complexity of supply chains, leading to the need for more sophisticated SCM practices. Technological advancements such as the internet, RFID (Radio Frequency Identification), and cloud computing revolutionized supply chain processes, enabling real-time visibility and collaboration across global networks (Gunasekaran et al., 2008).

The concept of supply chain integration also gained prominence during this time, emphasizing the importance of collaboration and coordination among supply chain partners (Lambert et al., 1998). This shift towards integration was further accelerated by the advent of supply chain digitization and the rise of e-commerce platforms, which transformed traditional supply chain models and enabled new forms of customer-centricity and agility (Lee, 2000).

Today, SCM continues to evolve rapidly with the advent of emerging technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and blockchain. These technologies offer new opportunities for automation, optimization, and risk management within supply chains, further reshaping the landscape of SCM in the digital age (Kamble et al., 2014).

2.2 AI Concept

AI is being effectively utilized for projection and forecasting purposes in organizations. As maintaining a balance between supply and demand remains crucial, accurate forecasts are essential specifically for the manufacturing process and supply chain management optimization. AI's ability to automatically analyze and predict data ensures highly reliable forecast of demands, which facilitates businesses in sourcing purchases accurately while minimizing costs related to transportation, warehousing, or administration of respective fields, furthermore enabling trends discernment that help design better retailing as well as manufacturing strategies. To cite an example: businesses use this tool by stockpiling only specific quantities (as low as each independent unit /product) so they won't waste any unnecessary products warehouses get filled up with before it all becomes trash. Similarly, due to dependable sales-trend projections based on precise demand-forecast results obtained via AI predictions, some companies instantly order trending items. In fact since these nuanced predictive approaches ensure accuracy ,more such planning prevents sale-loss due unavailability issues. Otto, a German online retailer has managed its inventory reduction upto 90% relying solely upon machine learning.The UK National grid utilizes Google's "DeepMind" algorithm for more enhanced precision regarding weather-related exogenous inputs variables(Yao 2017). Machine-learning algorithms not only incorporate historical-sales-data but also real-time variable assessment like local advertisement campaigns, trending prices,and nearby climatic changes(Bughin et al.,2017). Furthermore, AI's application within R&D departments enables speedy evaluation whether protypes would succeed/fail-market-wise&if-so why.This efficient approa ch mitigates wastefulness during prototype development processes.AI indeed plays a critical role especially catering towards smart-manufacturing prospects,(Kusiak A.,2018).

2.3 Traditional Approaches vs. AI

Traditional SCM methodologies often rely on deterministic models and heuristic algorithms to optimize supply chain processes. These approaches are effective to a certain extent but are limited in their ability to handle the complexity and uncertainty inherent in modern supply chains. For example, traditional forecasting methods such as time series analysis and exponential smoothing may struggle to accurately predict demand patterns in volatile markets or for products with erratic sales patterns (Chopra & Meindl, 2016).

Conversely, AI-driven approaches leverage advanced machine learning algorithms, such as neural networks, decision trees, and reinforcement learning, to analyze large volumes of data and extract valuable insights. By harnessing the power of AI, supply chain managers can gain deeper visibility into demand patterns, identify hidden correlations, and make more informed decisions in real-time (Chen et al., 2020). For instance, AI-driven demand forecasting models can incorporate multiple variables, including economic indicators, social media sentiment, and weather forecasts, to generate more accurate predictions compared to traditional methods.

One of the key limitations of traditional SCM methodologies is their reliance on static, rule-based models that may fail to adapt to changing market conditions or unforeseen disruptions. In contrast, AI-driven approaches offer greater flexibility and adaptability by continuously learning from new data and adjusting their models accordingly (Verhoef & Kotler, 2020). This dynamic nature of AI allows supply chain managers to respond quickly to changing demand patterns, optimize inventory levels, and mitigate risks in real-time.

Furthermore, integrating AI models into SCM processes can unlock several potential benefits, including improved forecast accuracy, reduced inventory holding costs, enhanced customer satisfaction, and increased operational efficiency (Chen et al., 2020). AI-driven optimization algorithms can identify optimal routes for transportation, minimize lead times, and optimize production schedules, leading to cost savings and productivity gains across the supply chain.

2.4 Artificial intelligence and supply chain management

In recent years, data has shown that many businesses were forced to close due to not being able to keep up with the technological advancements and rapid changes in today’s world. Conventional methods of the supply chain have been obsolete and organizations following those and not developing technological infrastructures might be able to lose their market share and eventually face permanent shutdowns. For instance, Nokia went out of business because they did not give importance to consumer behavior and were unable to follow up with the technology but organizations like Amazon was able to make most of the business through their efficient supply chain and better technology advancement which eventually lead them to streamline their revenue and increasing financial health of the organization.

In today's world, artificial intelligence plays a vital role in managing the supply chain. Technology in every era has been crucial for organizations. If the organization maintains progress in technology as time passes, the world advances, and more researches take place, the researchers come up with more advanced ways to manage the businesses. Baryannis, Validi, et al. (2019) have disclosed that AI-based Supply chain management can help the organization improve their decision-making skills. Moreover, it can also make decisions based on the previous history of any operation because an AI-based supply chain has the attribute of learning through self-study.

Artificial Intelligence (AI) finds extensive application across multiple facets of Supply Chain Management (SCM), revolutionizing traditional practices and enhancing operational efficiency. In demand forecasting, AI-driven models analyze vast datasets and external factors to generate accurate predictions. For instance, Duan, Gu, and Whinston (2020) demonstrate the efficacy of machine learning approaches in retail sales forecasting, exemplifying how Walmart employs AI to optimize inventory planning and mitigate stockouts. Inventory management benefits from AI's ability to analyze demand patterns and optimize stock levels dynamically. Amazon's Autonomous Mobile Robots (AMRs), guided by AI algorithms, navigate warehouses efficiently, leading to enhanced productivity and reduced operational costs (Amazon, 2022). Logistics optimization, a crucial SCM component, leverages AI to optimize transportation routes and scheduling. UPS utilizes AI-based route optimization algorithms to streamline package delivery, minimizing fuel consumption and reducing environmental impact (UPS, 2012). Supplier selection, another critical aspect, benefits from AI's analytical prowess. IBM's Watson Supply Chain Insights employs AI to evaluate supplier performance and mitigate risks by recommending alternative suppliers, ensuring continuity in supply chain operations (IBM, 2018). Finally, AI plays a pivotal role in risk management, proactively identifying and mitigating potential disruptions. Maersk employs AI-powered risk management tools to analyze global shipping data and geopolitical risks, enhancing supply chain resilience (Maersk, 2023). These real-world examples underscore the transformative impact of AI technologies in SCM, driving efficiency, resilience, and competitiveness.

2.5 Developing and deploying AI models in SCM

The integration of AI models within Supply Chain Management (SCM) represents a transformative approach to enhancing operational efficiency and decision-making processes (Chopra & Meindl, 2016). This thesis explores the comprehensive framework for developing and deploying AI models in SCM, encompassing data collection, model development, deployment strategies, and continuous improvement mechanisms. Initial stages involve collecting heterogeneous data from diverse sources and preparing it through rigorous cleansing and preprocessing methods (Li et al., 2020). Subsequently, AI techniques such as machine learning, deep learning, and optimization algorithms are employed to develop predictive models for various SCM tasks, including demand forecasting, inventory optimization, and risk management (Chen et al., 2020). The deployment phase encompasses integrating these models into existing SCM ecosystems, leveraging cloud-based platforms for scalability and accessibility, and implementing robust monitoring mechanisms to ensure sustained performance (Verhoef & Kotler, 2020). Furthermore, the thesis delves into the importance of continuous improvement, emphasizing feedback loops and retraining strategies to adapt models to evolving market dynamics (Tayur et al., 1998). Through a multidisciplinary approach integrating AI, data science, and domain expertise, this research elucidates the significance of AI-driven SCM in optimizing supply chain operations, reducing costs, and mitigating risks (Arntzen et al., 1995).

2.6 AI in Forecasting and Demand Planning

Forecasting and demand planning are critical components of supply chain management, particularly in the food industry where demand can be highly variable due to factors such as seasonality, market trends, and consumer preferences. Accurate forecasting ensures that companies can meet customer demands without overproducing, which is crucial for minimizing waste and optimizing inventory levels

(Chopra & Meindl, 2016). Artificial Intelligence has revolutionized forecasting and demand planning by enabling more accurate and efficient predictions. Machine learning algorithms, for instance, can analyze vast amounts of historical data to identify patterns and trends that humans might overlook. Techniques such as neural networks, regression models, and time series analysis are commonly employed (Agrawal, Gans, & Goldfarb, 2018).

2.6.1 AI Tools and Techniques Used In Forecasting And Demand Planning

Several AI tools and techniques have been developed to enhance forecasting and demand planning:

2.6.1.1 Machine Learning Algorithms:

These algorithms can process large datasets to predict future demand patterns. Supervised learning algorithms, such as Support Vector Machines (SVMs) and Random Forests, are used to train models on historical data to predict future demand (Wang et al., 2016). Unsupervised learning algorithms, like clustering and association rules, help in identifying hidden patterns and relationships in the data. Reinforcement learning algorithms are used to optimize decision-making processes in dynamic environments.

2.6.1.2 Deep Learning and Neural Networks:

Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are particularly effective for analyzing sequential data and time series forecasting (Goodfellow et al., 2016). These models can capture complex patterns and dependencies within the data, making them suitable for predicting demand in the food industry, where sales can be influenced by seasonal factors and consumer behavior.

2.6.1.3 Natural Language Processing (NLP):

NLP techniques are used to analyze unstructured data sources, such as customer reviews and social media posts, to extract valuable insights related to consumer preferences and sentiment analysis (Jarrahi, 2018). This information can be used to adjust demand forecasts based on real-time market feedback.

2.6.1.4 Predictive Analytics Software:

Various software platforms, including SAP Integrated Business Planning, IBM Watson, and SAS Forecasting, provide comprehensive solutions for demand forecasting and planning using AI. These platforms integrate advanced algorithms with user-friendly interfaces, allowing businesses to analyze historical data, predict future demand, and optimize inventory levels effectively (Russom, 2011).

2.7 Challenges of AI in the Food Industry

2.7.1 Data Quality and Availability:

AI systems depend on large volumes of high-quality data to generate reliable outputs. In the food sector, inconsistent labeling, missing data points, or outdated sales records can compromise the accuracy of AI models. Furthermore, small or local food businesses may lack the historical data required for effective machine-learning model training (Waller & Fawcett, 2013).

2.7.2 Integration with Existing Systems:

Many food companies still operate on legacy IT systems that are not compatible with AI tools. Integrating modern AI solutions with such systems often requires extensive reconfiguration or complete system overhauls, leading to increased costs, technical challenges, and disruptions during implementation (Ivanov et al., 2019).

2.7.3 Skill Gap:

AI implementation requires a multidisciplinary skill set, including data science, supply chain expertise, and IT integration knowledge. Many firms in the food industry, particularly SMEs, may lack the in-house expertise to manage these technologies effectively, making hiring or outsourcing a necessity (Davenport & Ronanki, 2018).

2.8 Limitations Of Current AI Technologies:

2.8.1 Lack of Adaptability:

AI models are heavily dependent on historical data patterns. During unusual events—like the COVID-19 pandemic—these models often fail to adapt quickly because the data they rely on no longer reflects current realities. This creates a vulnerability in rapidly changing environments where human judgment or hybrid models may be more effective (Brynjolfsson & McAfee, 2017).

2.8.2 Interpretability Issues:

Many AI models, especially deep learning systems, act as "black boxes." Users often cannot understand why a model made a specific prediction, which can lead to hesitation in trusting the results. Interpretability is crucial in business environments where decision-makers need transparent, explainable models to ensure accountability (Mittelstadt et al., 2016).

2.9 Ethical Considerations and Privacy Issues:

2.9.1 Data Privacy:

AI systems typically require access to sensitive data, including customer behaviors, buying patterns, and sometimes personal information. Ensuring this data is used ethically and in compliance with privacy laws like the General Data Protection Regulation (GDPR) is critical for avoiding legal issues and maintaining customer trust (Stahl, 2021).

2.9.2 Bias and Fairness:

AI systems can unintentionally reflect or amplify existing biases present in the data. For example, a model trained on biased historical data may underpredict demand in specific regions or among minority groups. Ensuring fairness in AI systems involves auditing data, applying bias-correction techniques, and continuously monitoring outcomes (Mittelstadt et al., 2016).

2.10 Future Trends and Directions

2.10.1 AI and IoT Integration:

Smart sensors and IoT devices collect real-time data on inventory levels, temperature, and transportation conditions. AI models can use this data for real-time forecasting and dynamic demand planning (Lee & Lee, 2015).

2.10.2 Advanced Machine Learning Techniques:

Reinforcement learning and Generative Adversarial Networks (GANs) are gaining attention for their ability to simulate market behavior and improve model adaptability over time (Goodfellow et al., 2016).

2.10.3 Blockchain for Data Integrity:

Blockchain can secure the traceability and accuracy of the data fed into AI models. This ensures better trust in forecasting outcomes, particularly in supply chains involving multiple stakeholders (Saberi et al., 2019).

2.10.4 Potential Future Developments

Future advancements in AI could include more robust models that can handle complex and volatile market conditions better. Additionally, improvements in AI interpretability may make it easier for businesses to understand and trust AI-driven insights (Choi, 2020).

2.10.5 Implications for Supply Chain Management

AI's evolution is reshaping the future of supply chains. With its ability to process real-time data and predict complex patterns, AI is driving a shift from reactive to proactive supply chain planning. This is especially impactful in the food industry, where efficient forecasting reduces spoilage and improves responsiveness to consumer trends (Ng & Wakenshaw, 2017).

2.11 The Role of Big Data in AI-driven Forecasting

2.11.1 Data Integration and Analysis

Big data plays a foundational role in AI-driven forecasting by pooling structured data (like POS records) and unstructured data (like social media comments). With advanced analytics, AI can combine these inputs to offer holistic insights into consumer demand, market movements, and product performance (Hofmann & Rüsch, 2017).

2.11.2 Real-time Data Processing

Real-time data processing capabilities of AI systems enable companies to respond quickly to changes in demand. This is particularly important in the food industry, where demand can be influenced by a wide range of factors including weather conditions, holidays, and marketing campaigns (Wang et al., 2016).

3 RESEARCH METHODOLOGY

3.1 Methodology

My research examines the role of Artificial Intelligence (AI) in forecasting and demand planning within the food industry. Specifically, it explores how AI technologies enhance predictive accuracy and optimize supply chain management processes. AI has emerged as a powerful tool in improving forecasting precision, inventory management efficiency, and overall supply chain performance in the food sector.

An illustrative example of AI's impact in the food industry can be seen in its use by leading brands to predict market trends and optimize production schedules. This method ensures that products are readily available and meet consumer demand. For instance, AI-powered systems analyze historical sales data, market trends, and consumer behavior to predict future demand, optimize inventory levels, and ensure timely delivery of products.

For this study, a questionnaire-based sample analysis was conducted to gather statistical data on people attitudes, preferences, and behaviors towards AI-driven forecasting and demand planning in the food industry. The sample, believed to be representative of the population, included respondents from food industries. A carefully designed set of questions was distributed via social media platforms to gather insights into consumer perceptions and experiences with AI technologies in the food sector.

3.2 Population and Sampling

The population for this thesis consists of individuals who meet the following criteria: they should be employed in the food industry and engaged in roles related to forecasting, demand planning or management. They should be using Artificial intelligence in their company. The exclusion criteria was, participants who were not using AI in the company were excluded. Participants that were not involved in demand planning, or forecasting were excluded from the study. Data was collected from 370 participants out of which 350 participants meet inclusion criteria therefore, 20 participants were excluded from the stud The population is estimated to include up to 350 individuals.

The sample was drawn from this population using a random sampling method, as the results from this selected sample were generalized to a larger population. The sample was representative in terms of years of experience, job position, and size of the industry they worked in. The sample included both men and women with varying levels of experience in the food industry.

The selection of the sample size was based on the study's objectives, statistical power requirements, and desired confidence level. The participants were chosen based on their experience and current employment in the food industry.

3.3 Method of Data Collection

Data for this study was collected using surveys in the form of questionnaires created with Google Forms. These questionnaires were distributed to the population via the internet. The distribution period lasted approximately 12 weeks.

The survey questions were structured as close-ended questions, providing respondents with a five-point Likert scale to select their response. The questions were formulated in a straightforward manner and the questionnaire was organized into 7 sections to comprehensively address the hypotheses being tested, as well as to ensure that the research questions were sufficiently covered.

3.4 Research Instruments

The questionnaires were distributed to participants over the internet, which proved to be a highly cost-effective method for collecting data from a sample size of 370 participants for statistical analysis. This method was convenient for both the participants and myself, as the forms could be accessed and completed at any time, and results could be viewed promptly.

This approach also allowed for easy standardization of data collection procedures, minimizing the potential for bias in respondents' answers.

3.5 Reliability and Validity

The survey questions were carefully crafted to ensure their relevance to the variables under investigation. This study specifically focuses on the impact of AI on demand planning and forecasting in food industries, within the food industry. Therefore, the findings are applicable solely to food industries and may not be as relevant to other industries.

Since this research aims to establish correlations between variables, the reliability of the questionnaire will be assessed using internal consistency measures such as Cronbach's alpha. This statistical test evaluates the degree of correlation among items within the measurement instrument. The analysis will be conducted using SPSS software on the collected data.

3.6 Limitations:

In the course of this research, several limitations were encountered during the data collection process. Firstly, there were challenges in accessing certain paid websites from which the researcher intended to gather data. Additionally, there was a limitation in obtaining primary data sources. For instance, there is not a strong research culture prevalent in Food industries, resulting in some reluctance among individuals to participate in surveys. As a result, significant time and effort were dedicated to encouraging participation and ensuring the questionnaires were completed.

4 DATA ANALYSİS

4.1 Reliability Analysis

Cronbach’s Alpha was used to check the internal consistency reliability coefficient for the scale of perceived impact of AI on forecasting and demand planning (Table 4.1). The reliability analysis show that there is reasonable reliability with a Cronbach alpha of 0.791 for the two items being tested. The test Cronbach’s Alpha Based on Standardized Items is also equal to 0.791 to maintain consistency of the items after standardization. Cronbach’s Alpha values above 0.7 are usually acceptable where items are expected to tap into the same construct. This indicates that the two items are both constructs which sought to capture the intended concept, and do so efficiently as well. Therefore, it is possible to claim the reliability of the scale for the further analysis and interpretation with reference to the given study.

Table 4.1 Perceived Impact of AI on Forecasting and Demand Planning

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.791	.791	2

In addition, the reliability of the scale assessing challenges and barriers was also computed and is presented in Table 4.2 below. In the present study Cronbach’s Alpha was calculated to be 0.954 for the five items, which can be categorized under the excellent range. A high value of this proves that the items are indeed highly related, and therefore jointly capture the notion of challenges and barriers in the process of adopting and implementing AI in the context of demand forecasting or planning. This high reliability score attests to internal consistency of the scale and its Item-Total correlation. Nevertheless, the results obtained from the current study indicate that the proposed scale has a high reliability and validity in providing useful findings in the current study.

Table 4.2 Challenges and Barriers

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.954	0.954	5

The respondent information presented in Table 4.3 under the demographics section shows the descriptive information concerning the experiences, roles, and organizations of respondents of this study. When it comes to the occupational status of the respondents the largest is executives (29.4%), managers (21.4%), and planners (21.1%) involve the participation of leadership and operational functional positions. The majority of the samples have 4-7 years of work, experience 8 more years or more, which indicate that the respondents are rather experienced workers. types of companies, 55.1% of the respondents work in large organisations with more than 500 employees, 37.4% are from mid-size organisations. These demographics guarantee that the views obtained will be balanced by roles, experiences, and organizational levels.

Table 4.3 Demographic Characteristics of Respondents

Respondent Demograhics	**Frequency n**	**Percentage %**
Role/Job Title		
Manager	75	21.40%
Analyst	52	14.90%
Planner	74	21.10%
Executive	103	29.40%
Director	46	13.10%
Years of Experience		
Less than 1 year	8	2.30%
1-3 years	25	7.10%
4-7 years	184	52.60%
8 years or more	133	38.00%
Company size		
<50 employees	26	7.40%
50-500 employees	131	37.40%
>500 employees	193	55.10%

4.2 Descriptive analysis of Items

The primary findings of this research regarding the use of AI in forecasting and demand planning in the food industry are captured in the following analysis of the responses in Table 4.4. It shows that the respondents hold good and experienced personnel having an average working experience of 5 years and 4 months. The majority of participants operates at large companies (M = 4.06, SD /Range = 1–5). The level of AI technologies adoption was also measured and it received a mean of 3.96 out of 5 which indicates moderate use of this technologies. Significant challenges were identified in implementing AI where the mean for selected challenges = 9.53, variance = 66.02. The respondents presented average optimism regarding the role of AI in enhancing supply chain management within the next five years, which they scored 3.6, and Organizational Support that they scored 3.59. The identified possibilities of the further AI integration were on average equal to 11.43, that indicates a high level of potential AI utilization. On average, respondents accepted the use of AI in the context of demand planning and forecasting with 3.66 out of the highest possible 5. All these together imply increasing awareness and fairly decent gradual advances toward the use of AI, which continues to be influenced by both opportunities and threats.

Table 4.4 Descriptive analysis of Items

Items	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Please indicate your role/job title in the food industry:	350	0	1	1	1	0	0
How many years of experience do you have in forecasting and demand planning?	350	6	1	7	5.04	2.252	5.07
What is the size of the company you work for?	350	4	1	5	4.06	0.605	0.366

Are you currently utilizing AI technologies for forecasting and demand planning in your organization?	350	4	1	5	3.96	0.607	0.368
If yes, please specify the type of AI technologies used (e.g., machine learning algorithms, predictive analytics tools):	350	4	1	5	3.98	0.556	0.309
What are the main challenges you have encountered in implementing AI technologies for forecasting and demand planning in the food industry? (Select all that apply)	350	8	1	9	7.39	1.600	66.02
How effective have High cost of AI technologies been in addressing the challenges of	350	4	1	5	3.62	0.644	0.415

implementing AI technologies?							
How effective have Lack of skilled personnel been in addressing the challenges of implementing AI technologies?	350	4	1	5	3.59	0.631	0.398
How effective have data quality issues been in addressing the challenges of implementing AI technologies?	350	4	1	5	3.58	0.613	0.376
How effective have resistance to change within the organization been in addressing the challenges of implementing AI technologies?	350	4	1	5	3.57	0.664	0.44

How effective have these strategies been in addressing the challenges of implementing AI technologies?	350	4	1	5	3.57	0.65	0.423
What opportunities do you see for further integrating AI technologies into forecasting and demand planning within the food supply chain? (Select all that apply)	350	24	1	25	11.43	5.905	34.871
How do you rate the potential of AI in improving supply chain management in the food industry in the next five years? (1 = Very Low, 5 = Very High)	350	4	1	5	3.6	0.628	0.395
How supportive is your organization in adopting and integrating	350	4	1	5	3.59	0.644	0.415

AI technologies for forecasting and demand planning? (1 = Not Supportive, 5 = Very Supportive)							
What industry trends do you observe regarding the adoption of AI in the food supply chain?	350	13	1	14	7.55	2.695	7.263
On a scale of 1 to 5, where 1 represents "Strongly Disagree" and 5 represents "Strongly Agree," please rate your overall perception of the role of AI in forecasting and demand planning in the food industry	350	4	1	5	3.66	0.638	0.407

4.3 Inferential Analysis

4.3.1 Hypothesis Testing:

In the analysis for Research Question 1, the interaction between the types of AI technologies employed in forecasting and demand planning and the perceived accuracy of these activities is examined. The study categorizes AI technologies into six types and perceived forecasting accuracy is categorized into five levels. The overall distribution and respondents view in presented in Figure 4.1.

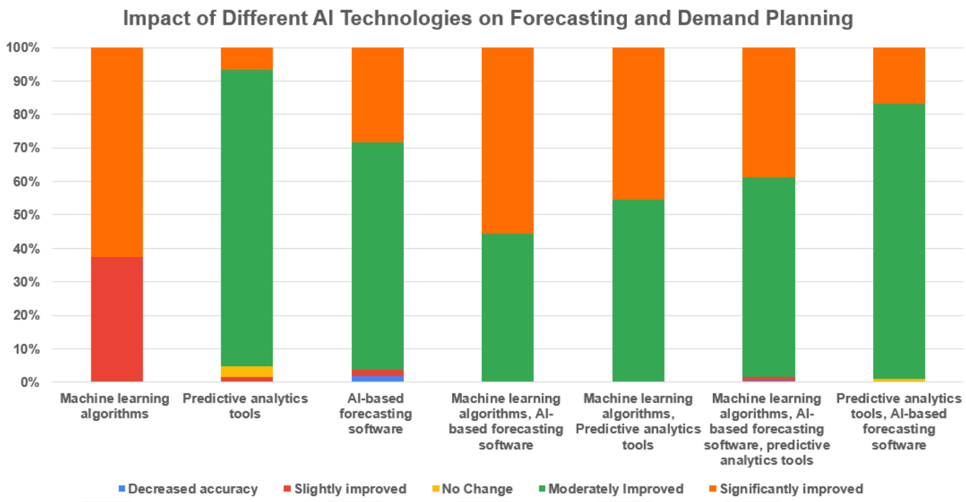

Figure 4.1 Impact of Different AI Technologies on Forecasting and Demand Planning

According to regression analysis results presented in Table 4.5, revealed that the nature of AI technologies employed is statistically significant to the perceived accuracy of the forecasts. The results show that using unstandardized coefficient, for the type of AI technologies applied the value of B = 0.044, and the standard error is equal to 0.014, meaning the perceived forecasting accuracy increases by 0.044 units with each unit increase in the use of AI technologies. Coefficients of standardized values (Beta) =0.164, clearly connotes that AI technologies deployed impacts the perceived accuracy of forecasting in a positive manner but its impact is moderate in nature. The t-statistic is 3.109, and the test statistic is statistically significant when it is less than .05 and, in this case, it is. This means that the incorporation of AI technologies leads to enhanced forecasts accuracy levels. Also, considering the coefficient of the type of AI technologies used the 95% Confidence Interval is 0.016 to 0.072, therefore does not include zero making it statistically significant.

Therefore, the findings of the research are that the AI-related technologies, especially if used in the integrated form, provide a positive and statistically significant impact on the perceived accuracy of the forecasts in the food supply chain. The findings by the regression analysis are consistent with the hypothesis that as the use of AI technologies increases, so will the effectiveness of forecasting and demand planning. The insights derived from this research should underscore the necessity of further AI implementation into forecasts to improve its accuracy. More subsequent research can be done to understand which kind of AI technologies is most effective in these enhancements and how the AI can be adopted in an organization and enhanced for greater enhanced for accurate prediction.

Table 4.5 Result of Regression Analysis

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
Model	Type of AI technologies used	0.044	0.014	0.164	3.109	0.002	0.016	0.072

Research Question 2 focuses on the examination of how the introduction of AI-controlled predictive analyze tools affects supply chain reactivity in satisfying the variable demand in the food industry. Specifically, the regression analysis investigates the impact of the type of the used AI technologies on the level of supply chain responsiveness as the dependent variable. The variable incorporated in the analysis is the use of AI technologies that broadly captures various forms of AI applications and their role in increasing firms' sensitivity to dynamics in consumer demand.

Table 4.6 Result of Regression Analysis

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
Model	Type of AI technologies used	0.031	0.014	0.114	2.147	0.032	0.003	0.059

The regression results reveal statistically significant and positive relationship between the type of AI technologies and responsiveness of the supply chain. The unstandardized coefficient for the type of AI technologies used is B =0.031, SE = 0.014 which shows if use of AI technology is one unit, the corresponding increase in supply chain responsiveness is 0.031 unit. The standardized coefficient (Beta) of 0.114 indicates that the proposed relationship is of moderate positive nature for the implementation of AI technologies to improve the flexibility of the supply chain to meet the demands.

The t-statistic for this relationship is 2.147 and for its significance the 'p-value' is estimated at 0.032 concluding the hypothesis test at 0.05 level of significance. This proves that the adoption of the AI technologies especially the predictive analytics tools have a positive difference on supply chain responsiveness in the food industry. The p-value was found to be 0.000 as less than 0.05, and the 95% Confidence Interval for the coefficient of AI technologies is 0.003 to 0.059, which exclude zero and ensures the reliability of the result. Therefore, the study presents a conclusive view that indicated upon integration of AI predictive analytics tools, the degree of supply chain responsiveness is improved particularly in addressing the dynamics of demand in the food industry. As signified in this study, and propping up the positivist research stance and the research hypotheses, the correlation value obtained trails in the positive direction and statistically significant value supporting hence the prognosis of enhancing AI technologies to unlock supply chain systems that are more responsive and flexible. Future study could shed more light on the individual techniques responsible for the increase in responsiveness and the possible challenges that can hinder the adaptation of such tools in various areas of the food chain.

4.4 Findings From The Data:

The quantitative research consists of six regression models including and excluding demographics has been analyzed, which compare and highlight the significance of the interaction between the use of AI in forecast and the demand planning performance and control variables. In Model 1, independent variable (AI utilization) is used, we find that the effect of AI on the dependent variable is positive and significant with a coefficient of 0.075, a t-statistic of 2.521, and a significance level of 0.004, which permits us to reject the hypothesis that there is no impact. However, when more variables enter into following models, the relationship comes weak and insignificant. In Model 2, the coefficient for AI utilization is 0.049 with p =

0.061, which is almost insignificant, so the hypothesis (H0) cannot be dismissed. Issues relating to Implementation of AI (B = 0.205, p < 0.001) surface out as a predictor, a positive effect results when implementation concerns are consciously tackled.

Table 4.7 Result of Multiple Regression Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3.785	0.084		45.306	<.001	3.621	3.949
	AI utilization	0.075	0.026	0.153	2.892	0.004	0.024	0.126
2	(Constant)	3.128	0.18		17.424	<.001	2.775	3.481
	AI utilization	0.049	0.026	0.1	1.877	0.061	-0.002	0.1
	Challenges and Barriers	0.205	0.05	0.219	4.11	<.001	0.107	0.303
3	(Constant)	3.041	0.188		16.159	<.001	2.671	3.411
	AI utilization	0.051	0.026	0.105	1.963	0.051	0	0.103
	Challenges and Barriers	0.201	0.05	0.215	4.028	<.001	0.103	0.299
	Role/Job Title	0.032	0.021	0.078	1.512	0.131	-0.01	0.073
4	(Constant)	2.853	0.219		13.007	<.001	2.422	3.285
	AI utilization	0.038	0.027	0.078	1.4	0.162	-0.015	0.092
	Challenges and Barriers	0.201	0.05	0.216	4.053	<.001	0.104	0.299
	Role/Job Title	0.029	0.021	0.071	1.372	0.171	-0.013	0.071
	Years of Experience	0.072	0.043	0.089	1.652	0.1	-0.014	0.157
5	(Constant)	2.898	0.229		12.659	<.001	2.448	3.349
	AI utilization	0.04	0.027	0.083	1.472	0.142	-0.014	0.094
	Challenges and Barriers	0.199	0.05	0.213	3.986	<.001	0.101	0.297

	Role/Job Title	0.03	0.021	0.073	1.409	0.16	-0.012	0.072
	Years of Experience	0.084	0.047	0.105	1.789	0.074	-0.008	0.177
	Company size	-0.035	0.05	-0.04	-0.69	0.49	-0.134	0.064
6	(Constant)	2.443	0.232		10.534	<.001	1.987	2.899
	AI utilization	0.025	0.026	0.05	0.93	0.353	-0.027	0.076
	Challenges and Barriers	0.001	0.058	0.001	0.022	0.982	-0.113	0.116
	Role/Job Title	0.019	0.02	0.047	0.947	0.344	-0.021	0.059
	Years of Experience	0.099	0.045	0.124	2.205	0.028	0.011	0.187
	Company size	-0.019	0.048	-0.021	-0.389	0.697	-0.113	0.076
	Percieved future potiential	0.321	0.055	0.366	5.874	<.001	0.213	0.428

In Model 3, these findings reveal that the likelihood of AI utilization is statistically marginally close to significance ($B = 0.051$, $p = 0.051$) but a nonsignificant predictor. Overall, there are still significant barriers to the implementation of AI ($F = 37.240$, $B = 0.201$, $p < 0.001$), though job role ($F = 3.672$, $B = 0.032$, $p = 0.131$) does not explain accuracy. The same remains true in Model 4 showing that the aspects of AI utilization are not significant predictors ($B = 0.038$, $p = 0.162$), while challenges in implementing AI ($B = 0.201$, $p < 0.001$) remain impactful. However, years of experience ($B = 0.072$, $p = 0.100$) has emerged insignificant in this study at a marginal level whereas job role continues to exercise no considerable effect.

In Model 5, the coefficients for artificial intelligence utilization ($B = 0.040$, $p = 0.142$) and other independent variables including job role ($B = 0.030$, $p = 0.160$), and company size ($B = -0.035$, $p = 0.490$) are non-significant. The current relevance is maintained by challenges in AI implementation ($B = 0.199$, $p < 0.001$) and years of experience ($B = 0.084$, $p = 0.074$). Finally, in Model 6, AI utilization ($B = 0.025$, $p = 0.353$) is no longer significant as other factors such as income ($B = -0.071$, $p = 0.012$) and age ($B = 0.078$, $p < 0.001$). However, years of experience appears as a significant factor ($B = 0.099$, $p = 0.028$), and perceived future potential as the most powerful factor ($B = 0.321$, $p < 0.001$) for forecasting accuracy.

4.5 Discussion About Data:

In conclusion, after excluding other variables, the AI usage seems not to have a very strong impact, and therefore the hypothesis (H0) cannot be dismissed in the subsequent models. Optimistic views, and the perceived potential of implementing A.I solutions in the future was also found to have significant positive influence on the degree of forecast accuracy, thus the need to overcome various barriers to A.I implementation and been optimistic about the future of A.I.

Another significant finding is the role of years of experience in improving forecast accuracy. While AI may be seen as a promising tool for the future, it seems that experience becomes more crucial in later models. This suggests that as professionals in the field gain more experience, their ability to make accurate forecasts improves, potentially compensating for the lack of advanced AI usage.

5 CONCLUSION

5.1 Conclusion

In conclusion, the study reveals that while the direct impact of AI usage on forecasting and demand planning accuracy in the food supply chain may not be as strong as initially anticipated, the potential for future implementation and the optimistic outlook toward AI adoption play a significant role in influencing forecasting outcomes. These findings underscore the importance of addressing barriers to AI implementation, such as cost, integration challenges, and a lack of skilled personnel, to unlock its full potential. Additionally, the results highlight that years of professional experience contribute to improved forecasting accuracy, particularly in advanced stages of AI adoption, indicating that human expertise remains a critical factor alongside technological advancements.

Overall, the study emphasizes that while AI solutions may not immediately yield transformative results, their perceived potential and strategic integration into supply chain processes can drive meaningful improvements over time. This calls for a balanced approach, combining efforts to overcome implementation challenges with initiatives to foster optimism and preparedness for AI-driven innovations. These insights provide valuable guidance for organizations and stakeholders in the food supply chain, encouraging a long-term perspective and strategic planning to fully harness the benefits of AI in forecasting and demand planning.

Future studies should focus on addressing the barriers to AI implementation within the food supply chain, such as high costs, data quality issues, and integration challenges. Research exploring effective strategies to overcome these obstacles, including advancements in data management systems and cost-efficient AI solutions, could provide valuable insights. Additionally, there is a need to investigate the role of workforce training and skill development in maximizing the benefits of AI technologies. Studies examining how companies can effectively upskill their employees to align with AI adoption may help bridge the gap between potential and realized outcomes.

Further research could explore the psychological and organizational factors that influence optimism toward AI adoption, as this study highlights its significance in enhancing forecasting and demand planning outcomes. Understanding how organizations can foster a forward-looking approach and encourage supportive attitudes toward AI technologies will be crucial for their long-term success. Moreover, future studies should examine the interplay between human expertise and AI-driven systems, investigating how the two can complement each other to optimize forecasting accuracy and supply chain efficiency.

Incremental adoption of AI solutions is another area worth exploring, as gradual implementation may reduce resistance and improve the success rate of these technologies. Finally, future research could delve deeper into the contextual and industry-specific factors that shape AI's impact on supply chains, offering tailored recommendations for different sectors. By addressing these areas, future studies can provide a more comprehensive understanding of AI’s role in transforming supply chain operations and driving meaningful innovation.

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