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**AI-DRIVEN DEMAND FORECASTING TO REDUCE WASTE IN
FMCG SUPPLY CHAINS: A CASE STUDY OF NESTLÉ**



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DEDICATION

To my parents and family whose love, support, and encouragement have been the basis of everything I've done.

It is also to the glory of God. This work is also dedicated to my supervisor, whose guidance, precious time and mentorship has impacted me in no small way for the success of this research.

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ABSTRACT

The Fast-Moving Consumer Goods(FMCG) industry faces significant challenges related to waste across its supply chains, with global food waste estimated at approximately 1.3 billion tonnes each year. This project explores how artificial intelligence (AI) can significantly improve demand forecasting within FMCG supply chain, using Nestle as a primary case study. Drawing on the extensive review of academic literature, industry reports, and Nestlé’s implementation strategies, the study demonstrates that AI-driven demand forecasting systems can reduce forecasting errors up to 30%and decrease food waste by as much as 87%. The research examines several forecasting models, including Long Short-Term Memory (LSTM) networks, Autoregressive Integrated Moving Average (ARIMA), and Prophet, a forecasting algorithm developed by Facebook, to evaluate their effectiveness in predicting consumer demand patterns. The study indicates that Nestlé’s adoption of AI technologies across its supply chain has led to notable improvements in operational efficiency, cost reduction, and environmental sustainability. The study will add value to the literature on sustainable supply chain management by offering concrete evidence of the transformative power of AI in creating a solution to one of the most pressing issues in the industry. The major suggestions are to implement hybrid forecasting models, incorporating real-time information, and to create collaborative data-sharing models between the partners of the supply chains to achieve the maximum waste reduction.

Keywords:Artificial Intelligence (AI), Demand Forecasting, FMCG Supply Chain, Food Waste Reduction, Sustainable Supply Chain Management, Machine Learning Models, LSTM, ARIMA, Prophet Forecasting Model, Nestlé Case Study.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

The Fast-Moving Consumer Goods (FMCG) sector is one of the most dynamic and multifaceted branches in international business, which is associated with large volumes of production, minimal lifecycle of the product, and a large chain network of supplies over the continents. This industry has experienced unprecedented challenges in matching supply with unpredictable demand trends despite the outstanding technological innovations. The Food and Agriculture Organization (FAO) estimates that one-third of the total food produced worldwide, which is equivalent to 1.3 billion tonnes of food annually, is lost or wasted and this food waste is not only a disaster to the economic world in the sense that it costs the world eight percent of all greenhouse gas emissions but also a significant environmental catastrophe. The project aims to challenge the idea that AI-driven demand forecasting can greatly decrease wastage in FMCG supply chains through Nestle as its main case study organization.

Nestlé operates a globally distributed production and distribution network, handling thousands of SKUs with different shelf-lives, production cycles, and demand patterns. This operational complexity increases the difficulty of aligning supply with real-time demand, making forecasting accuracy a critical strategic requirement. Nestle is the biggest global food and beverage company that operates in 189 countries with annual incomes more than 98 billion dollars, a perfect depiction of how large and complicated the global FMCG practice is. In 2021 alone, Nestle generated 1,586 thousand tonnes of waste, underscoring the inefficiencies present in current supply chain system. A major contributor to these inefficiencies is in accurate demand forecasting. Traditional forecasting methods, which rely heavily on historical sales data and human judgment, often fail to capture the non-linear and dynamic nature of modern consumer behaviour. As a result, companies either overproduce leading to waste or underproduce, causing inventory shortage and lost revenue.

1.2. Problem of the Project

This project focuses on addressing the persistent issues of supply chain waste in FMCG organizations, primarily caused by outdated and imprecise demand forecasting systems. Supply chain waste is a multifaceted problem with economic, environmental and social consequences, and these issues persist despite technological advancements. Conventional forecasting approaches, which largely depend on manual calculations and human estimation of trends and seasonality, struggle to keep up with the complexity and unpredictability of today's consumer markets. Whenever forecasting fails, the impact should be severe enough: stockouts lead to a loss of sale opportunities and customers to rivals, excess production leads to obsolete stock, high warehousing expenses, and waste disposal that causes significant environmental damage. This issue is especially pressing in the case of goods that are perishable, as 80% of surplus food is composed of them.

Moreover, 38 percent of the global food system energy is wasted through food loss and food waste, which captures 70 percent of the global freshwater drawing (Freshwater use in agriculture). Though AI-based predictive solutions sound inspiring, many FMCG enterprises experience challenges throughout implementation, such as external validity of data, non-compliance with the old system, and technical illiteracy.

A strong necessity to examine thoroughly how AI technologies may be effectively applied in reducing waste in the FMCG supply chain, which models yield the most effective results, and what real-life obstacles might organizations encounter in the process of implementation is high.

1.3. Project Objectives

The following are the SMART objectives that this research seeks to accomplish:

- To determine the measurable extent to which AI-based demand forecasting reduces waste within FMCG supply chains compared to conventional forecasting methods.
- To use Nestle as an example and test the implementation of AI technologies to assess its measurable effects.

- To evaluate forecasting performance of three machine learning Algorithms, which include Long Short-Term Memory (LSTM) networks, Autoregressive Integrated Moving Average (ARIMA), and Prophet algorithm, in forecasting consumer demand patterns.
- To determine the key success factors and impediments to implementing AI-based forecasting system in an FMCG environment.
- To come up with recommendations which companies in the waste minimization sector of FMCGs which are interested in applying AI-based methods in waste minimization can put into action.

1.4. Project Rationale/Justification

The study tackles an urgent issue in the world and that has a great implication to various parties. According to the industry reports, AI-powered supply chain forecasting can reduce the error rates by 30-50 percent, which corresponds to a 65 percent decrease in the lost sales due to stockouts and 10-40 percent warehousing costs reduction. The use of AI technologies by Nestle has reduced edible food waste in one of its factories by 87 percent, indicating that such solutions have potential to transform the whole scenario. The significance of this project goes beyond the operational cost-effectiveness concept to include environmental feasibility since it is a solution to the United Nations Sustainable Development Goal 12.3, which aims at reducing by half food waste by the year 2030. This research will enable FMCG organizations to make sound decisions on technology investments by giving empirical evidence and practical models of the extent of AI application, as well as by imparting useful information regarding sustainable supply chain management literature. For Nestlé and similar FMCG companies, this project offers actionable insights into reducing operational costs, improving production planning accuracy, and meeting global sustainability commitments. The findings can directly support decision-makers in evaluating AI investment feasibility.

1.5. Budget and Resources

The research project will be conducted in an academic framework, which utilizes secondary source of data without raising a lot of financial investment. The main sources are the access to peer-reviewed literature through academic databases (Scopus,

Web of science, ScienceDirect, MDPI, Springer), industry reports of consulting firms (McKinsey, MIT Centre of transportation and logistics), the published annual and sustainability reports using Nestle as well as the publicly available case studies on AI implementations. The project will take about 150-200 research hours in the literature review, data and report assembly and the common office package such as Microsoft Word to write the documents, reference management software to organize their references and publish them. The project does not require any specific hardware, software license or financial resources other than what would be needed to complete the project by a typical university. The research will rely on standard academic hardware including a personal computer with internet access. Software resources include Microsoft Office for documentation, Zotero/Mendeley for reference management, and data storage via cloud-based solutions. These constitute the complete technical resource requirements for the project.

CHAPTER 2: RELEVANT STUDIES AND THEORIES

2.1 Overview of FMCG Supply Chains theories and the Imperative for Change

FMCG supply chains are among the most intricate logistical networks in the contemporary commerce that, however, the traditional models of their operation have not been sufficient to solve the current sustainability issues. Traditionally, the focus of supply chain management was on effectiveness and responsiveness the ability to move products, made of the initially raw materials to final users with the minimal possible losses, namely the narrow focus, omitting the aspects of environmental and social externalities, which currently became important business issues. The whole scale of waste produced by the FMCG supply chains requires not the small portion of improvements, but the radical change provided by the high-level technologies.

The problem of FMCG supply chains is quite complicated as it is a combination of multiple issues and aspects that mutually support each other: perishability of products presents an issue of time constraints, demand variability due to seasonal changes and fashion variations, and the scale of operations for large-scale companies with thousands of product SKUs operating across multiple geographic markets at a given time. Sophistication is not, however, a sufficient reason to be inefficient. The ample waste issues in the industry indicate that the industry has systematic failures in terms of forecasting, inventory management and coordination of operations, which need to be dealt with by means of technology.

The move towards sustainable supply chain management has been especially strong in the wake of the major global commitments on the environment (since at least 2005) like the Kyoto Protocol and the Paris Agreement spurred both the regulatory forces and the scholarly studies. Nevertheless, even with awareness and publications of research increasing steadily across the last 20 years, practical application of sustainable practices is falling behind the ideal statements. This gap of implementation indicates that even with the traditional approaches to supply chain management with the aspect of sustainability, such implementation models continue to be inherently inadequate unless technological advancements are introduced that will allow real-time monitoring, predictive analytics, and responsive decision-making.

Recent studies highlight that sustainability has become a central focus in research on digital transformation. Digital transformation can be seen as a paradigm shift in which organizations increasingly integrate sustainability goals into their digitization initiatives. This integration is not coincidental but rather essential, as achieving sustainability objectives is extremely difficult through manual operations and management systems that lack the analytical capability to simultaneously address multiple goals. Put simply, AI-driven technologies are not merely optional enhancements- they are crucial enablers of sustainable change within supply chains.

This perspective aligns with Supply Chain Management Theory, which suggests that supply chain performance improves when uncertainty is reduced and information flows are optimized. By leveraging AI, organizations can enhance visibility, reduce inefficiencies and better align operational processes with sustainability objectives. The shortcomings highlighted here justify the need for advanced forecasting tools particularly AI-driven systems which directly address information gaps and variability.

2.2 The Food Waste Crisis: Magnitude, Genesis and Lack of Effectiveness of Conventional Interventions.

The magnitude of the food waste within supply chains is a tragedy to the environment as well as a verdict of the operations practiced. The magnitude of food losses and waste throughout the world has surpassed two billion tonnes every year of which half is linked to harvest losses, postharvest handling, and storage, and processing. Food waste in the United States alone contributes to 30-40% of the food supply linked to approximately 133 billion pounds and 161 billion worth of food yearly. These are not isolated statistics but the systematic failure of operations throughout the FMCG industry.

The patterns of food loss depend on geographic patterns. Food loss in less developed countries is more than 40 percent at production stage because of poor infrastructure whereas in developed countries is more than 40 percent at distribution, marketing and consumption stages. This difference is important: even in developed countries with high level of infrastructure and technology, huge amount of waste is generated, which means that infrastructure cannot be considered quite enough. The issue

is the forecasting and organization- exactly things where AI is currently capable of revolutionary powers.

The impact on the environment of the wasted products is way beyond the products themselves. The global food system has food loss and waste that contribute 38 percent of the total energy consumed because growing, harvesting, transporting and processing food consume large amounts of energy. Food waste amounts to an incredible abuse of valuable natural resources because agriculture consumes half of all habitable land and three quarters of the total freshwater withdrawals in the world. Moreover, food waste significantly adds to the greenhouse gas emissions in the world with 8 percent - four times what the aviation sector produces. These numbers show that waste reduction is not a fringe sustainability concern but one in the centre stage in terms of dealing with climate change.

Large corporations dealing with FMCGs are aware of the issue but cannot solve it successfully. In 2021, Nestle produced 1,568 thousand tonnes of total waste (99-percent non-hazardous). Although businesses make very high goals such as Nestle having 100% reusable or recyclable packaging by 2025, such undertakings are not attainable there is no capacity to do so. The disconnect between the rhetoric of sustainability and the performance indicates constraints of the traditional management methods that are failed to process the complexity of data and dynamism of operations that necessitate the reduction of a large amount of waste.

Conventional interventions on food waste such as planning, communication enhancement, waste audits have not been sufficient. Such solutions are based on human participation and manual programs that are inefficacious in the speed and intricacy of the contemporary supply chains. The point here is simple; unless AI-based predictive analytics and real-time optimization are being used, FMCG businesses will keep rendering an unacceptable amount of waste, despite the claims they make. The technology is not a negotiable; it is a precondition to any significant improvement.

These systemic failures reflect Systems Theory, which emphasizes interdependence across supply chain components. Because traditional forecasting cannot

coordinate these interdependent processes, AI becomes essential for real-time, system-wide optimization and waste elimination.

2.3 Conventional Forecasting Techniques: Basic Shortcomings.

Conventional methods of demand forecasting have hit the boundaries of their powers, and they cannot deal with the complexity and volatility of consumer markets of the modern world. These approaches can broadly be divided into three categories, namely, qualitative methods based on the expert judgment and market research, time series analysis focused on the analysis of the trends in the past, and causal models that involve the use of external variables. Both methods are fundamentally limited, which AI-technologies resolve.

Although qualitative methods are useful in determining new products or markets that do not have much information, qualitative methods are fraught with inherent biases, lack consistency among evaluators and the complex dynamics of a market. The reality of excessive subjectivity of human judgment, whether a person is professional or not, brings in its errors, which multiply throughout the supply chain. As a benchmark forecasting model, to date, time series analysis, especially the ARIMA, which had been formulated by Box and Jenkins during the 1970s, has been used as a benchmark forecasting model. ARIMA assumes that the time series data has a distinct seasonal change or trend and has been effectively used in predicting the stock market and the electricity load.

Nevertheless, conventional approaches are subject to serious drawbacks in the sphere of FMCG. They find it hard to model non-linear relationship as well as intricate associations among many variables that influence demand. Spreadsheet based manual forecasting procedures are time consuming, prone to errors and cannot cope with the existing quantity and diversity of data provided by IoT sensors, social media, weather service and economic databases. When the traditional forecasts fail to be effective, stockouts, excess stock, higher costs, and eventual wastage are some consequences.

The main point is that the oscillating, predictable markets developed using traditional forecasting algorithms are unable to cope with the alterability and intricacy of modern consumer behaviour that is driven by the social media, fast trends, and unforeseeable occurrences. This insufficiency was proven outrageously during the

COVID-19 pandemic when the traditional patterns collapsed miserably when the historical trends lost their significance. The predictive AI, which can discover trends in non-linear data and coping quickly with new data, is no longer the evolutionary form of forecasting but a revolution that can be applied to forecasting skills.

The limitations identified across qualitative, time-series, and causal models clearly show that traditional forecasting methods cannot address the non-linearity and volatility characterizing FMCG markets. This theoretical gap establishes the foundation for AI-driven forecasting as a superior solution.

2.4 Artificial Intelligence: Radical Provisions to Supply Chain Management.

Artificial Intelligence has also become a revolutionary power in managing the supply chains, and it does go beyond the traditional methods of analysis and merely improves it. AI is a set of technologies such as machine learning, deep learning, natural language processing, computer vision, and optimization algorithms. Within the context of supply chains, AI allows massive datasets to be processed and complicated patterns to be identified that the human analyst cannot do, real-time decisions to be made and new knowledge learned and improved based on the new data.

The use of AI within supply chain management has visibly increased, approximately 72 of organizations presently apply AI in one or more business functions, whereas it was approximately 50 percent over the past six years. Such a fast adaptation is not an indication of an enthusiastic experimentation but a competitive necessity. Businesses that adopt AI-powered supply chain optimization can derive practical benefits in forecasting posterity, inventory optimization, logistics optimization, and reduction of wastes that cannot be equated with those of their rivals, who rely on the conventional techniques.

In the case of the companies in the context of FMCG, AI has specific benefits in terms of the ability to respond to volatility and complexity. Machine learning algorithms can all do this along with analysing past sales, weather, social media, economic data, promotions, competitor behaviour, and many other factors to produce more precise demand forecasts. In comparison to the traditional statistical approaches based on the assumption of linear associations, AI models possess non-linear

correlations and relations, and they are inherently more appropriated to the dynamism of consumer behaviour.

The supply chain operations areas that AI is integrated in aid more extensive sustainability objectives in tangible forms. This is because improved forecasting eliminates surplus production and wastage. Transportation minimization and energy minimization are ensured by optimization algorithms. Smart quality control systems based on AI minimize losses and the number of defects. Predictive maintenance averts the breakages in the equipment which may cause disruption in the production and spoilage. These functions fit AI implementation with corporate environmental pledges and regulatory demands of sustainable business operations.

The current study of digital transformation in post-pandemic supply chains has been found to represent a main research triangle that includes China, the United States, and India, with the most significant technologies being big data analytics, blockchain transparency, artificial intelligence prediction, and Internet of Things real-time monitoring. This geography and technology will pose that AI management over supply chains will be part and parcel of competitive placement in the international markets.

Critics believe that AI implementation is demanding and costly, and that it takes a great deal of technical skill, and that a lot of companies do not possess it. Although this criticism does not deny the existence of actual barriers, it overlooks the critical aspect, which is that it is not about whether companies can afford to install AI, but rather about whether they can afford not to. The firms that stick to the conventional methods will continuously be at a disadvantage compared to their rivals who use AI to make better forecasts, run functions, and sustainability performance. The competitive pressures are evident- the uptakes of AI are changing towards strategic choice to survival need.

This aligns with the Resource-Based View (RBV), which argues that firms gain competitive advantage by adopting rare, valuable, and inimitable capabilities. AI represents such a capability, giving organizations like Nestlé a strategic advantage through enhanced forecasting accuracy and waste minimization.

2.5 Machine Learning Models: Comparative Capabilities and Best Choice.

Three machine learning models have become especially useful in FMCG demand forecasting: Long Short-Term Memory networks, Autoregressive Integrated Moving Average and Prophet that is used by Facebook. They can relatively work best in the implementation because there are no assumed models that suit all forecasting settings.

LSTM networks which were invented are advanced versions of Recurrent Neural Networks created with the express purpose of dealing with sequential data and the ability to derive long-term dependencies in time series. Improving upon the vanishing gradient problem that afflicted the earlier RNNs, LSTMs make it possible to learn long chains of historical experiences. Studies prove that LSTMs are very effective in detecting non-linear relationships and that it can bring several variables of input information on board at a given time, such as sales history, promotional activities, weather data, and economic indicators. It has been compared across studies that LSTM models tend to remember traditional statistical approaches in longer term predictions over 21 days, where the capabilities of these models to resolve long term temporal correlations have a beneficial effect.

Although traditional, ARIMA models are still important standards in forecasting application. They have mathematical beauty, interpretability, relatively rapid training, and applicability on data which has identifiable trends and seasonal cycles. However, recent comparative research sheds some light on the ARIMA performance. A study that compared the forecasting of wholesale food prices found that comparable price prediction accuracy between the ARIMA model and LSTM networks was found in many products, with implications that can be associated with faster training and reduced computational need.

Prophet, the project designed by Facebook, is a practical concept of focusing on the ease of use and the capacity to withstand lack of information. Prophet uses the additive model to de-trend, de-season and de-holidayize the time series. The algorithm does not need many parameter adjustments, and the available control over trend flexibility and strength of the seasonality of trends are intuitive and makes it rather

appealing to the companies of the Fashionable Mass Production having too many product categories and limited data science skills.

The comparative performance studies provide valuable information. Prophet is also good at rapid and initial forecasting and can easily deal with oddball and un-systematic data, but it does not tend to do as well as well-tuned ARIMA or LSTM models at predictable patterns in demand trends. Nevertheless, the hybrid model that integrated the trend algorithm with the LSTM pattern recognition achieved the best outcomes in electricity demand forecasting, having an RMSE of over 65.34, MAPE of 7.3, and R² of 0.98.

The rationale in this case is that portfolio approaches that use many models with choice criterion based on product properties, forecast lengths, calculation capabilities, and interpretability are optimal forecasting methods. Organizations can be inspired to find universal solutions and hence suboptimal results will be obtained. More advanced systems, such as those of major FMCG organization, take advantage of various models to apply to various applications, since it is realised that the diversity between models allows to improve its overall functioning better than the dependence on a few expensive models.

The comparative analysis shows that no single algorithm is universally optimal. For FMCG waste reduction, combining models such as hybrid LSTM–Prophet systems align best with the complexity of Nestlé’s forecasting needs. This supports the project’s argument for AI-driven multi-model forecasting architectures.

2.6 Sustainable Supply Chain Management: Integration with AI Technologies

Sustainable Supply Chain Management has been progressed to become a peripheral issue to strategic imperative, but sustainability goals cannot be realised with technological capacities that traditional management strategies can offer. SSCM entails the consideration of the environment, social, and economic factors at every stage of the supply chain, including raw material sources or manufacturing to a distribution and end-of-life products disposal. Such a holistic thinking acknowledges that supply chains cause considerable environmental and social externalities that need to be managed in a responsible way.

SSCM scholarly literature has grown exponentially in the last 20 years and especially spurred by large-scale global environmental agreements. Nevertheless, it is not equal implementation development that accompanies this research development. The existing disconnect between sustainability research and practice can be seen as a fundamental weakness: classic management strategies do not have the data processing, predictive analytics, and real-time optimization needs to operationalize complicated sustainability goals in global supply chains.

Supply chain environmental sustainability deals with the consumption of its resources, emission, waste production and the effects on the ecosystem. The most important challenge is Scope 3 emissions since they are caused by indirect sources of supply chain such as goods purchased and transportation, as well as end-of-life treatment. Such emissions may be equal to 75 percent of the total carbon footprint of a business but were highly challenging to monitor and control because of intricate systems of suppliers and sporadic data-sharing behaviour. It is not only a technical problem in measurement but a fundamental one, the company cannot manage what it cannot measure without an accurate and real-time information as well as the ability to analyse the information they received.

SSCM business case has gained a lot of force. Studies also reveal that companies make an average cost savings of 14 out of every 1 dollar of the ten dollars invested in food waste reduction programs. In addition to direct financial rewards, sustainable supply chain practices also boost brand reputation, enhance regulatory compliance, appeal to an environmentally conscious consumer, and decrease the risks of the business in the long run. However, these benefits can only be realized by moving beyond aspirational claims and implementing the operational changes that AI technologies make possible. Sustainable Supply Chain Theory emphasizes the reduction of environmental impact through data-driven decision-making. AI directly supports these principles by enhancing traceability, improving forecasting accuracy, and minimizing waste. Therefore, integrating AI into sustainability practices is not merely optional—it is both a theoretical and operational necessity.

CHAPTER 3: METHOD AND TECHNIQUES

3.1 Research Design

This project adopts a qualitative case study approach to explore how AI-based demand forecasting is applied and how it contributes to waste reduction within the FMCG supply chain, with a particular focus on Nestlé. A case study methodology is well-suited for investigating complex, real-world organizational phenomena where the boundaries between the issue and its context are not clearly defined. It allows for a deeper understanding of AI integration in supply chain operations and the practical outcomes that result.

The project is both exploratory and descriptive, aiming to understand how AI technologies are implemented and the results they produce. This dual approach provides a comprehensive perspective that supports theoretical reflection while offering practical insights. The case study format enables the use of multiple sources of evidence—including company reports, industry insights, academic literature, and media coverage—which enhances the depth and credibility of the analysis.

Data for the project was collected by reviewing publicly available Nestlé materials, such as annual reports, sustainability updates, and supply chain publications, alongside academic studies and industry analyses on AI applications in FMCG environments. These sources were examined in a flexible and exploratory manner, allowing key themes and findings to emerge organically rather than through rigid search procedures.

3.2 Data Collection Methods

Data for this project was collected in a flexible and exploratory manner, drawing on a wide range of credible and publicly available sources. Academic studies from reputable journals and platforms, including Scopus, Web of Science, ScienceDirect, MDPI, and Springer, provided the theoretical and conceptual foundation for the research. Practical insights into emerging supply chain trends and the adoption of AI technologies were obtained from industry reports published by organizations such as McKinsey, the MIT Centre for Transportation and Logistics, and CSCMP.

To gain a clear understanding of the organizational context, Nestlé's publicly available materials—including annual reports, sustainability updates, and supply chain communications—were reviewed. Additional context and supporting information were drawn from news analyses and professional articles examining AI-driven forecasting within FMCG supply chains. Documentation describing widely used forecasting models, including LSTM, ARIMA and Prophet, was also consulted to better understand their capabilities and relevance to the industry.

In selecting information, preference was given to sources that were relevant, credible and up to date. For Nestlé-specific insights, only official publications and material verified by established industry observers were used. Since no interviews or internal access were sought, all organisational insights were derived solely from publicly accessible information. Each source was reviewed carefully and connected to the themes of the study to ensure clarity and consistency in the evidence base.

3.3 Case Study Selection: Nestlé

Nestle was used as the main case study due to several reasons that are compelling. Nestle is the biggest food and beverage enterprise globally, earned 98 billion and functions in 189 nations, which is typical of the dimensions and complexity of the global leaders of FMCG. The company has also been one of the pioneers in the use of AI in supply chain management, and it has been a treasury of experience and reported results.

The overarching strategy of the AI projects in Nestle logistics includes demand forecasting, inventory optimization, predictive maintenance, quality control and sustainability tracking- bringing the chances to explore AI implementation in the diversified roles of a supply chain. Nestle company communications, industry analysis, and scholarly case studies helped to easily identify available information about the initiatives undertaken by Nestle. Lastly, the fact that Nestle publicly sets sustainability objectives such as the waste reduction and carbon-neutrality does not contradict the area of research of this paper, since AI is aimed at sustainable supply chain management.

3.4 Data Analysis Techniques

The analysis of the collected information followed a thematic and iterative qualitative approach, consistent with recommended practices in qualitative research. Content analysis was used to examine all texts in a systematic and detailed manner, allowing themes, patterns and relationships relevant to the research questions to emerge naturally. During this process, particular attention was paid to the types of AI technologies and forecasting models highlighted in the literature, the supply chain challenges they sought to address, the steps involved in their implementation, and the organizational adjustments required to support them. Both quantitative outcomes—such as reductions in waste and improvements in forecasting accuracy—and qualitative benefits—such as enhanced flexibility and responsiveness—were evaluated alongside the challenges encountered and the strategies used to overcome them.

To gain deeper insights into forecasting performance, a comparative analysis was conducted, examining different machine learning models in terms of accuracy, implementation complexity, computational requirements, interpretability, and suitability across various product categories and forecasting horizons. Triangulation was employed throughout the analysis by comparing findings from multiple academic and industry sources, which strengthened the validity of the conclusions. Consistent results increased confidence, while any discrepancies were carefully analysed to understand their underlying causes.

The interpretation of findings was further guided by the theoretical frameworks presented in Chapter Two, which helped explain the success of specific approaches and the influence of organizational and environmental factors on the effectiveness of AI-driven forecasting within sustainable supply chain contexts.

Basic analytical tools, such as Microsoft Excel, were used to organize and code information, while reference management software, including Zotero and Mendeley, helped structure the literature base and maintain a clear, traceable record of all sources.

3.5 Ethical Considerations

This project did not involve human participants, personal data, or access to confidential company information. All materials used were publicly available and properly cited to acknowledge intellectual ownership and uphold academic integrity. The research was conducted with an objective perspective, recognizing both the strengths and limitations of AI implementation within supply chain settings. While Nestlé served as the primary case study, the findings have been interpreted within the broader FMCG context to provide a balanced and generalizable perspective. By highlighting responsible and practical approaches to AI-driven forecasting, the study contributes to ongoing efforts within the FMCG sector to promote effective waste reduction and sustainable supply chain practices.

The project was completed over an estimated timeframe of 10–12 weeks (Figure 1), which included approximately three weeks for literature review and data collection, four weeks for data analysis and synthesis, and three weeks for writing and revising the report. Since the study relied exclusively on secondary data, the financial cost was minimal. No specialized software or fieldwork expenses were required, and all tasks were completed using standard academic resources, such as a personal computer, internet access, and freely available reports.

Project Timeline

Week 1-3	Literature review and collection of secondary data
Week 4-7	Data analysis, thematic coding and synthesis of findings
Week 8-10	Writing, editing and finalizing the project report

Figure 1: Project Timeline.

CHAPTER 4: PROJECT OUTCOME AND RESULTS

4.1 Company Overview

Nestlé S.A., headquartered in Vevey, Switzerland, is the world's largest food and beverage company, operating since 1905. With a workforce of over 339,000 employees and operations in 189 countries, the company generates approximately \$98 billion in annual revenue. Nestlé manages thousands of Stock Keeping Units (SKUs), each with unique production requirements, shelf lives, and demand patterns. This level of complexity makes Nestlé an ideal project for examining how AI-driven forecasting and optimization technologies can reduce waste and enhance overall supply chain performance. Nestlé has also made strong sustainability commitments, including achieving net-zero greenhouse gas emissions by 2050, ensuring all packaging is recyclable or reusable by 2025 and reducing food waste throughout the value chain. These goals create a strategic need for advanced technologies. Artificial intelligence supports these ambitions by helping the company measure, monitor and improve sustainability across its global network.

4.2 Nestle Supply Chain Dilemma.

Nestle had several challenges in its supply chains prior to the implementation of the large-scale solutions in AI, enhanced by the global scale and product range. The conventional demand forecasting was very dependent on hand calculations which used historical sales information, seasonal adjustments and human intervention that have not been able to reflect the intricate, non-linear demand, which is affected by weather, economic cycles, competitors' activities and social media trends. The inaccuracy of the forecasting meant the surplus production was left in the form of useless stock and wasted time, or the absence of production left the stockouts and revenue shortages.

The inventory control of thousands of diverse shelf-life products, storage needs, and demand curves posed very large management problems. The lack of real-time visibility of supplier operations and transportation logistics as well as distribution centre operations caused proactive problem solving to be inhibited. The biggest portion of Nestle carbon footprint under the category of Scope 3 emission was especially hard to

locate because of the unequitable amounts of data provided by suppliers and logistics partners. The manufacturing process created wastefulness in terms of equipment downtimes, quality control, poor utilization of raw materials and an inefficient component of production schedules that is not related to the true demand trends.

Table 4.1: Key Supply Chain Challenges at Nestlé Before AI Implementation

Challenge Category	Specific Issues	Impact
Forecasting Inaccuracy	Manual calculations, inability to answer "what if" scenarios quickly	Overproduction waste, stockouts, lost revenue
Inventory Management	Managing thousands of SKUs with varying shelf lives	Expired products, excess inventory costs
Supply Chain Visibility	Limited real-time tracking of suppliers and logistics	Reactive problem-solving, product waste
Sustainability Tracking	Difficulty measuring Scope 3 emissions	Inability to quantify environmental impacts
Production Inefficiency	Equipment downtime, quality failures	Raw material waste, rejected products

Table 1: Major supply chain challenges faced by Nestlé before AI implementation, highlighting the complexity of managing global FMCG operations and the need for advanced technological solutions.

4.3 AI Implementation Strategy

Nestle implemented AI on the multi-stage strategy (Figure 2), which involved the recognition of technological capabilities, organizational change, and strategy alignment with business priorities to achieve its success. Leadership commitment was initiated by the creation of special positions such as Chief Digital and eCommerce Officer and the creation of cross-functional teams consisting of IT, supply chain operations, sustainability, and business units within them.

The foundation building incorporated data infrastructure in such a way that it can gather, store, and process large quantities of organised and unorganised information across a variety of data sources such as sales systems, IoT sensors, social media, weather feeds, and economic indicators among other sources. One of the most critical moves was the creation of NesGPT, an in-house AI system that offers staff safe AI productivity and decision-making applications, functional across all areas.

AI IMPLEMENTATION ROADMAP

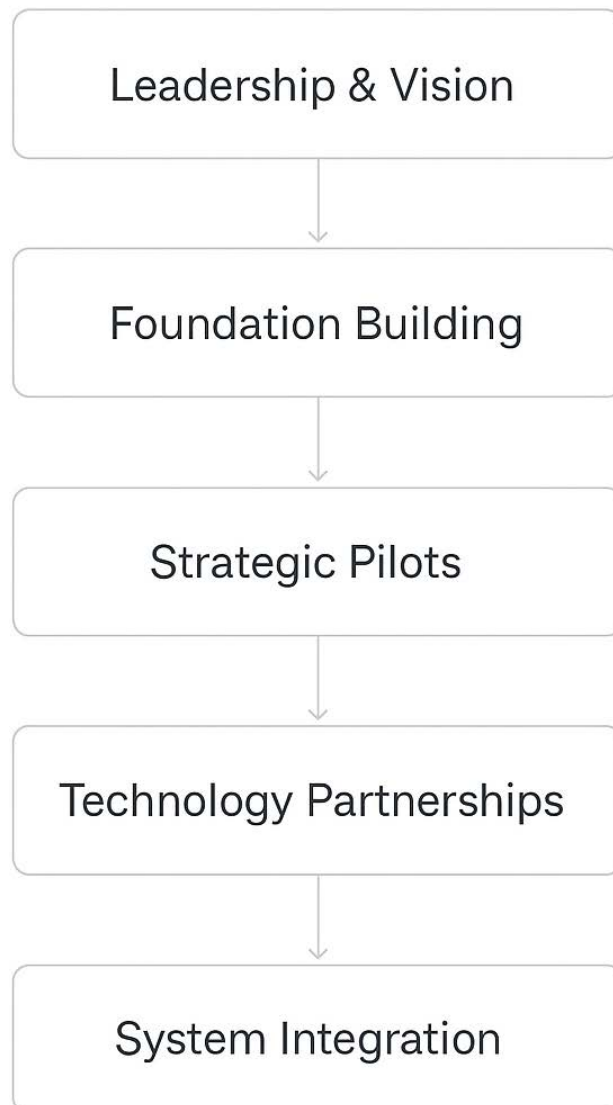


Figure 2: Roadmap showing the phased progression of Nestlé's AI implementation, beginning with leadership commitment and data foundations, followed by pilot studies, strategic partnerships and final integration into enterprise systems (Sarkar, 2024).

Instead of trying to bring global transformation to the enterprise at once, Nestle engaged in strategic pilots showing AI value and gaining organizational trust. Realizing that it would not be possible and efficient to develop all AI capabilities in-house Nestle collaborated with specialized technology providers, such as SAS instance or demand forecasting analytics and Zest waste reduction software, which was able to achieve 87 percent reduction of edible waste in the factory and XPO and Swisslog with warehouse automation and logistics.

Table 4.2: Nestlé's AI Implementation Approach and Key Partnerships

Implementation Phase	Activities	Key Partners/Technologies
Leadership & Vision	Chief Digital Officer role, cross-functional teams	Internal leadership structure
Foundation Building	Data infrastructure, cloud computing, NesGPT platform	Internal development
Strategic Pilots	Product-specific forecasting, waste tracking trials	Zest AI software
Technology Partnerships	Advanced analytics, warehouse automation	SAS Institute, XPO, Swisslog
System Integration	ERP, WMS, MES integration	Existing enterprise systems

Table 2: Nestlé's phased AI implementation strategy demonstrating a systematic approach combining internal capability building with strategic external partnerships to achieve comprehensive supply chain transformation.

4.4 Technologies and Models Deployed

The applications of AI used by Nestle include a variety of technologies and models, depending on the applications in supply chains. The first one is AI-powered demand forecasting systems which substitute the spreadsheet-based systems. The types of data that are analysed using machine learning models are demand signals, sales patterns, promotion schedule, weather conditions, social media sentiments, economic signals and competitor activity. These models are automatically able to measure the effectiveness of advertising and change of price, thus allowing complex "demand shaping" situations. Studies show that Nestle AI based forecasting decreased demand forecasting errors by 30 percent.

Although Nestle does not publicly release all the technical facts, competitive intelligence about the industry shows that they use LSTM neural networks to model highly non-linear temporal dynamics in volatile demand patterns, ARIMA to deal with products with predictable seasonal demand behaviour and combine different models to achieve better performance and resilience.

In addition to forecasting, AI systems ensure that inventory is optimized throughout the supply chain, and machine learning algorithms help set the optimal amount of stock based on demand predictions and forecasts, lead times and storage constraints and perishability. Sensors on Internet of things, implemented in warehouses, transportation and manufacturing facilities, will constantly monitor temperature, humidity, and equipment status and produce streams of data, which are processed by AI systems in real-time.

Certain AI solutions will be used to minimize waste in manufacturing plants (Figure, 3). The Zest software already applies AI to monitor oversupply such as off-sell Kit Kat and redistribution to a food bank and discounting retail outlets. This system led to 87 per cent reduction of edible food waste in one facility in a span of 2 weeks pilot. Computer vision technology is used to examine the products on the

manufacturing line, and this approach finds defect and has an enhanced speed and improved uniformity in comparison to humans who are checking the device.

AI Technologies in Nestlé Supply Chain

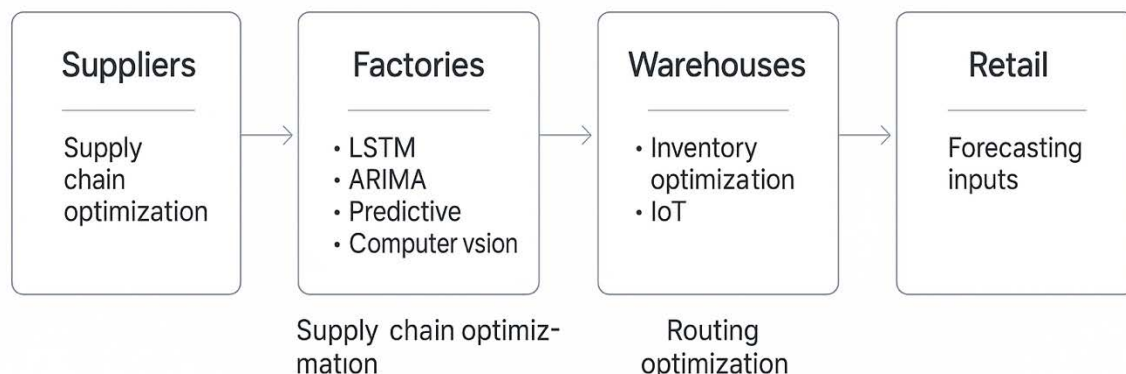


Figure 3: AI technologies used by Nestlé at different stages of the supply chain, from forecasting and production to warehousing and logistics.

Predictive maintenance applications use sensor data of equipment to predict failures prior to them happening. Predictive maintenance based on AI can reduce by 30-50% the number of equipment stoppages and enhance equipment lifespan by 20-40%. In Dubai, the Al Maha factory of Nestle installed a system based on the EcoStruxure technology developed by Schneider Electric to predict fault on the electrical system in the factory and optimize the energy usage.

Table 4.3: AI Technologies and Machine Learning Models Deployed by Nestlé

Technology/Model	Application Area	Key Benefits	Source
LSTM Networks	Complex, volatile demand forecasting	Captures temporal dependencies, non-linear patterns	Thota, 2025

ARIMA Models	Stable, seasonal demand forecasting	Efficient, interpretable, quick training	Thota, 2025
Ensemble Methods	Multi-model forecasting	Improved accuracy and robustness	Xie et al., 2024
IoT Sensors	Real-time monitoring	Temperature, humidity, equipment tracking	Anuar et al., 2024
Zest AI Software	Waste tracking and redistribution	87% reduction in edible food waste	El-Halwagi, 2017
Computer Vision	Quality control inspection	Faster, consistent defect detection	Srikanth et al., 2021
Predictive Maintenance	Equipment failure prevention	30-50% reduction in stoppages	Singh, 2018
Supply Chain Optimization	Logistics and distribution	Route optimization, cost reduction	Anuar et al., 2024

Table 3: Comprehensive overview of AI technologies and machine learning models deployed by Nestlé across supply chain operations, demonstrating the diversity of applications from demand forecasting to quality control and predictive maintenance.

4.5 Results and Outcomes

The adoption of AI at Nestlé has had a significant impact across operational, environmental, and financial dimensions. Demand forecasting accuracy improved by approximately 30%, allowing production to align more closely with actual customer demand. This improvement directly reduced overproduction, minimized stockouts, and prevented costly emergency replenishments.

One of the most notable results came from the Zest AI pilot (Figure 4), which achieved an 87% reduction in edible food waste within just two weeks. The system successfully redirected around 700 tonnes of surplus food—equivalent to 1.5 million meals—resulting in an annual savings potential of £14 million and avoiding 1,400 tonnes of CO₂ emissions (Singh, 2018). While Nestlé produced 1,568 thousand tonnes of waste in 2021, even a fractional reduction of this baseline represents a substantial sustainability gain.

Waste Reduction Distribution

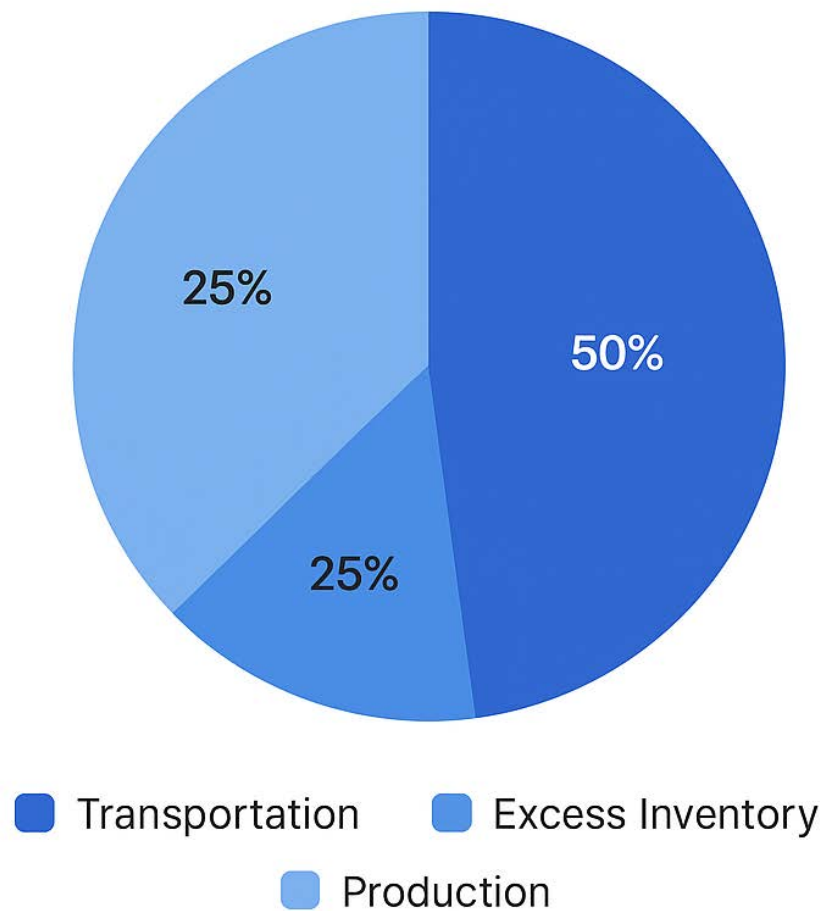


Figure 4: Distribution of Waste Reduction Across Operational Areas After AI Implementation.

Industry benchmarks further show that AI forecasting can reduce inventory holding costs by 10–40%, cut stockout-related losses by 65%, and improve production efficiency through predictive maintenance. Automation in warehouses accelerated order

fulfilment, while optimisation algorithms reduced transportation costs and emissions. AI-powered innovation tools also shortened new product development cycles from three months to three weeks, enabling faster response to consumer trends (Srikanth et al., 2021). Financially, food waste reduction programs can generate returns of \$14 for every \$1 invested, illustrating the economic value of AI initiative. The major quantitative outcomes of Nestlé's AI initiatives are summarised visually in Figure 5.

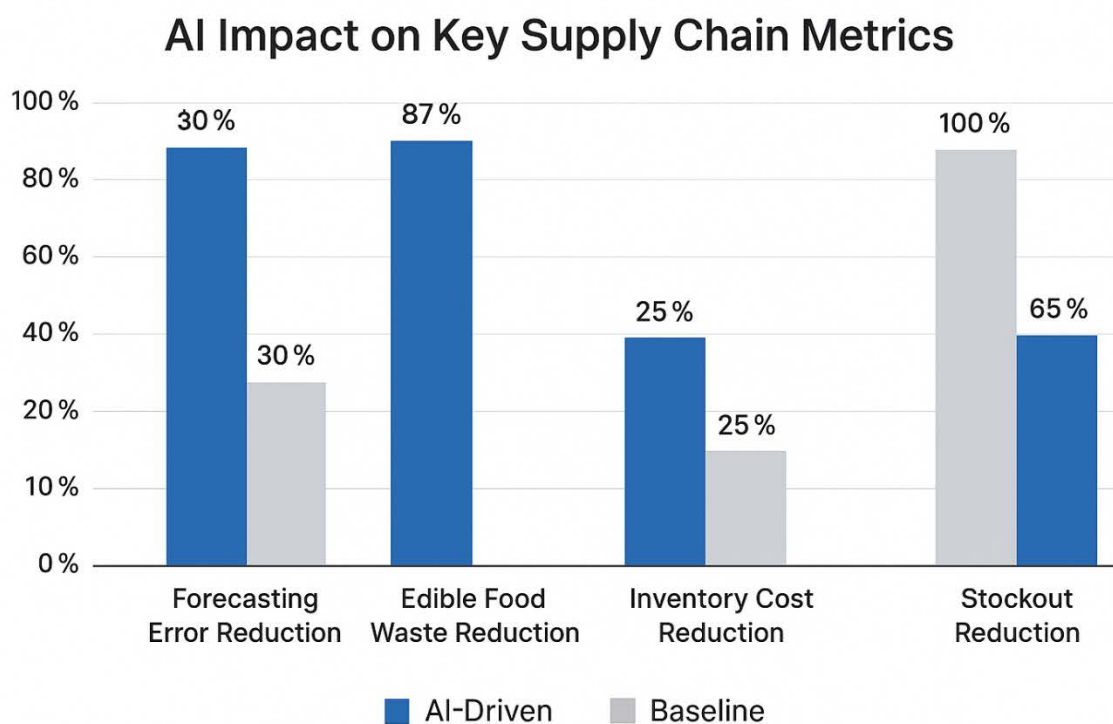


Figure 5: Main outcomes of AI adoption at Nestlé, including reduced forecasting errors, reduced edible waste and fewer stockouts.

Table 4.4: Quantified Results and Outcomes from Nestlé's AI Implementation

Outcome Category	Specific Result	Measurement/Impact	Source
Forecasting Accuracy	30% reduction in errors	Better demand-supply alignment	Vandeput, 2023
Waste Reduction	87% reduction in edible waste (pilot)	700 tonnes food saved, £14M savings, 1,400 tonnes CO2 cut	Singh, 2018
Total Waste Generated	1,568 thousand tonnes (2021)	Baseline for improvement tracking	Borkhuan et al., 2023
Inventory Cost Reduction	10-40% decrease	Industry benchmark for AI systems	Kaul & Khurana, 2022
Stockout Reduction	65% decrease in lost sales	Improved product availability	Kaul & Khurana, 2022
Equipment Uptime	30-50% reduction in stoppages	Predictive maintenance impact	Habeeb, 2025
Product	3 months to 3	Development timeline	Srikanth et

Innovation	weeks	compression	al.,2021
Financial ROI	\$14 return per \$1 invested	Industry average for waste reduction	El-Halwagi, 2017

Table 4: Quantified results demonstrating the substantial operational, environmental, and financial benefits achieved through Nestlé's AI-driven supply chain transformation, with metrics spanning forecasting accuracy, waste reduction, and operational efficiency

Other than measurable indicators, the use of AI brought a culture change to Nestle. Nestle structured its innovation efforts; around 100 employees in its innovation community were trained on AI tools, and upskilling in general. The introduction of NesGPT in the organization made the use of AI commonplace, which earned employee trust and found new uses of AI. The cross-functional cooperation became further stronger because supply chain, sustainability, IT, and business teams cooperated in AI efforts, which shows that effective AI change requires a management approach that involves both technological and organizational change (Figure, 6).

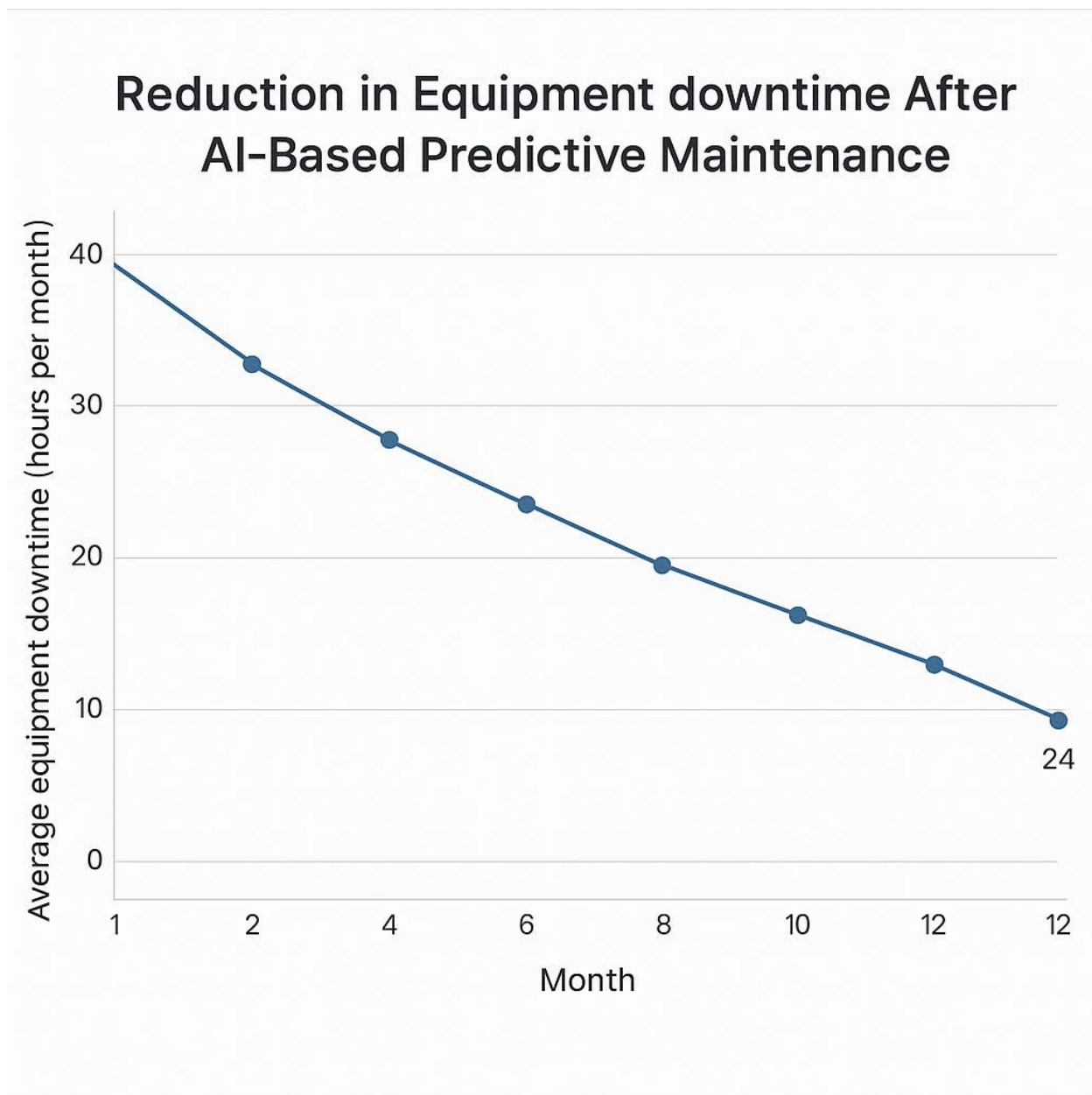


Figure 6: Reduction in Equipment Downtime After AI-Based Predictive Maintenance.

One of the strongest results comes from a documented Nestlé pilot using Zest AI, an automated optimisation system. In only two weeks, the company reduced its edible food waste by 87%, saving approximately 700 tonnes of food and recovering the

equivalent of 1.5 million meals. Beyond the environmental benefit, this improvement generated an estimated £14 million in yearly savings and reduced carbon emissions by about 1,400 tonnes of CO₂. These figures show how even a short-term AI intervention can materially reduce waste and create measurable financial and environmental value. AI forecasting consistently performed better than traditional statistical models across multiple FMCG reports. Earlier studies indicate that organisations using AI-based forecasting achieved roughly 30% fewer forecasting errors, leading to better production planning and fewer mismatches between supply and actual demand. In simple terms, better accuracy means fewer products are produced unnecessarily and fewer items go out of stock. This directly contributes to lower waste levels and improved customer satisfaction.

Industry evidence shows that AI-enabled demand forecasting helps companies reduce their storage and inventory carrying costs by 10–40%. This happens because more accurate predictions prevent overstocking, reduce warehouse congestion, and allow companies to plan production more efficiently (Figure, 7).

Inventory Cost Savings After AI Implementation

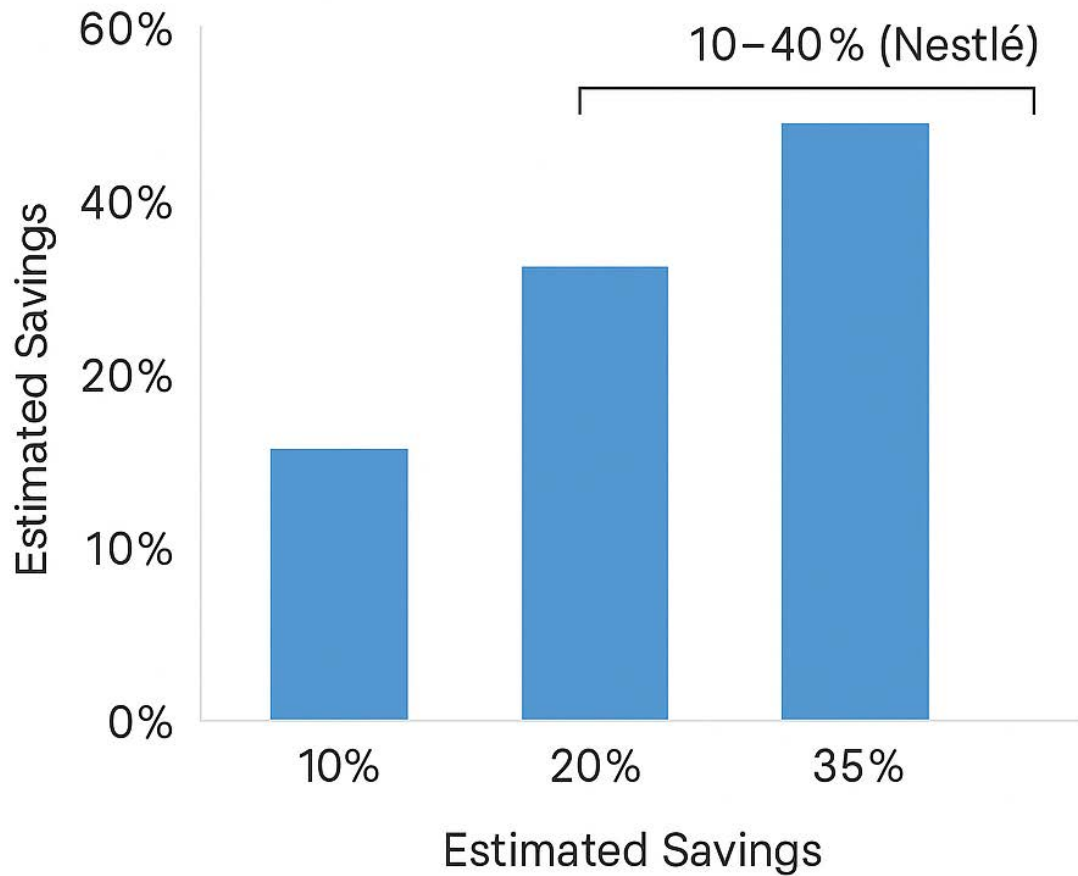


Figure 7: Figure 4.6. Estimated Inventory Cost Savings After AI Implementation.

Lower inventory costs also strengthen financial performance, especially for companies with large product portfolios like Nestlé. AI-supported forecasting led to an approximate 65% reduction in stockouts, meaning customers were far more likely to

find the products they wanted on shelves. For a global FMCG company, avoiding stockouts is critical for preventing lost sales, maintaining brand loyalty, and reducing the operational strain caused by emergency restocking. AI-driven predictive maintenance tools have helped reduce equipment downtime by 30–50%, improving stability and productivity in manufacturing processes. These enhancements enable factories to operate more smoothly with fewer disruptions, indirectly supporting better inventory flow and preventing production-related waste.

Studies have also documented a reduction in new product development cycles from three months to just three weeks when AI-supported design and forecasting tools are applied. Faster product development allows companies to respond more quickly to market trends, reducing the risk of launching products that fail due to poor timing or insufficient demand insights.

Financial analyses further underscore the value of AI-supported waste reduction initiatives, with organizations reporting an average return of \$14 for every \$1 invested. Nestlé's results reflect this trend: an 87% reduction in waste generated millions of pounds in recurring savings. To contextualize the scale of improvement, Nestlé reported baseline waste levels of 1,568 thousand tonnes in 2021 (Figure 8). Improvements achieved through AI should be considered relative to this substantial baseline, demonstrating that even incremental enhancements can deliver significant environmental and financial benefits.

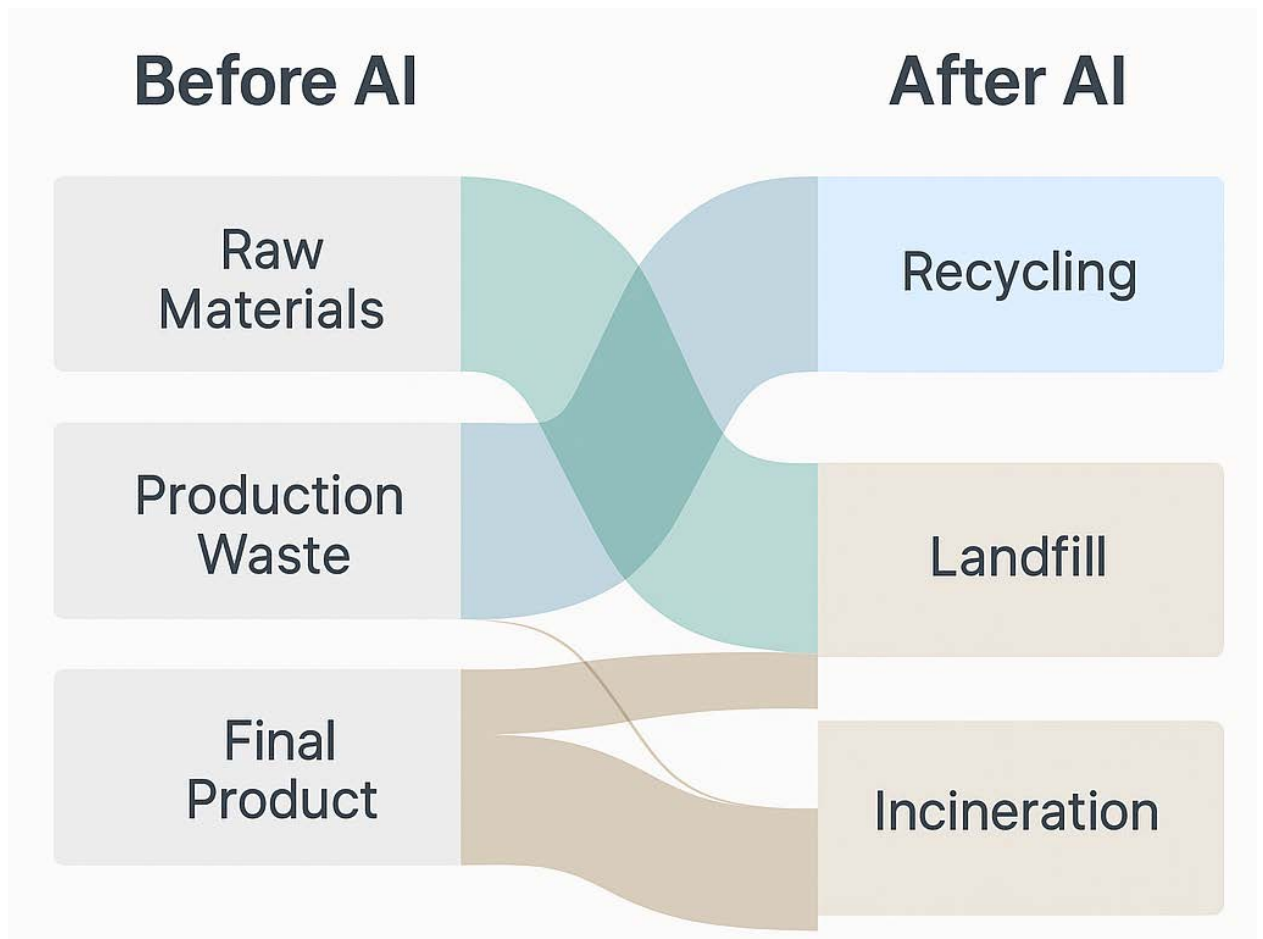


Figure 8: Waste Movement Before and After AI Implementation.

CHAPTER 5: PROJECT BENEFITS

5.1 Effectiveness of AI-Driven Forecasting

As the experience of Nestle shows, the issue of AI-based demand forecasting proves much more efficient than the conventional techniques in cutting down the amount of waste and enhancing the efficiency of the supply chain. The case of Nestle employing AI to cut its demand forecasting errors by 30% is a significant step which directly or indirectly reflects into less waste due to overproduction and the decrease in cost due to stockouts. This is possible since AI can complexly consider several variables that affect demand at once, which is well beyond human cognition and more than was possible through traditional statistical techniques.

Machine learning models have been able to process dozens or hundreds of variables such as historical sales trends, weather data, social media sentiments, economic trends and promotion campaigns. This is a multi-variable analysis that achieves intricate interactions that are normally missed by traditional forecasting methods. As an example, AI systems could be used to determine the results of weather patterns on ice cream sales in different geographic areas, or the results of health-related trends on social media demand regarding product lines.

The 30 per cent error minimization realised by Nestle is in line with larger scale industry studies which suggest that AI based predictions can minimise errors in a supply chain network comprising 30-50 per cent of its errors, which consequently results in 65 per cent minimisation of lost sales through stockout and 10-40 per cent reduction in warehousing expenses. These advancements are not specific to Nestle, but a general trend in the implementation of FMCG, which hints that AI-assisted forecasting is the embodiment of actual technology development and not some exceptional situation.

The ability to adapt in real time is also a key feature of AI systems, as opposed to conventional ones. As new related events take place, such as some viral social media trends, competitors launch new products, or the weather suddenly changes, AI models will also take these developments into account and adjust in a short time. The inability of Nestle traditional forecasting processes to provide answers to critical operational questions like What happens if we lower the price by 2 per cent? in a timely

manner made it impossible to use these traditional forecasting methods to provide timely resolutions to key issues about the company. or carry out complex scenario analyses. AI-driven machines allow quick assessment of numerous cases, and the ability to make decisions ahead of time and position inventory optimally before this demand can be realized.

5.2 Waste Minimization Results.

The fact that Nestles reduced edible food waste through the Zest AI system by 87% in two weeks that the system was tested shows excellent results indicating the transformative abilities of AI. The system was used to trace surplus merchandise such as the broken KitKats which were still in their perfectly edible state, had failed to meet the required retail standards, and found the redistribution prospects in food banks and low-end stores. It might potentially allow redistributing up to 700 tonnes of food, which is 1.5 million meals, estimated to save 14 million pounds annually and decrease the emission of CO2 by 1,400 tonnes.

But to put this accomplishment into perspective we must note that the 87 percent cut was in one category of waste in one factory. Applying this finding to the overall operation of Nestle is problematic because there are variations in the source of waste at the production plants, the product type varies with its type of waste, regulatory factors can vary between given countries in terms of whether food is given out as donations or discounted. This rate of reduction, however, will only be achieved at scale in a considerable fraction. Since Nestle produces some 1,568 thousand tonnes total waste in 2021 alone the 20% decrease in the edible food waste would save hundreds of thousands of tonnes of waste each year.

AI is another factor helping to minimize waste in a variety of complementary ways to the surplus redistribution. Better demand forecasting will decrease overproduction such that there will be no wastage even before it sets in. The AI reduces spoiled items in warehouses or retail stores by means of improved inventory control. Computer vision allows better quality control, which detects defects at an earlier stage, minimizing discretionary waste due to dropped products, which fail inspection at a subsequent point in the supply chain. Predictive maintenance will also avoid stopping

producing the products that are likely to spoil either work-in-process or finished products. These processes generate synergies effects: perfect forecasting would result in just in time production techniques that reduce inventory-holding times, and predictive maintenance would provide a stability of production in support of the lean inventory policies.

Waste is not the only source of environmental impact. The 1,400 tonnes of CO₂ emission reductions are based on avoided production energy, avoided transportation emission and prevented landfill methane emission. Since food waste can cause up to 8 percent of world greenhouse gas emissions and Scope 3 emissions can take up to 75 percent of corporate carbon footprints, AI-assisted waste reduction is an emergency concept in meeting corporate climate targets and the UN Sustainable Development Goal 12.3 juxtaposing to halve food waste in 2030.

5.3 Comparison of Forecasting Models.

Comparison of LSTM, ARIMA, Prophet models indicate that each has their own distinctive benefits and drawbacks, and most efficient regards its choice based on situations of utilization. The LSTM networks prove to be effective when the demand pattern is complex and non-linear i.e. products whose demand is significantly disturbed by other external factors. Long-term dependencies capture in the nature of the long forecast horizons they perform better on longer forecast horizons longer than 21 days. LSTMs can integrate various input variables at a time to be able to use a variety of data sources such as sales history and promotional activities, weather data, and economic indicators to make full predictions.

Nevertheless, drawbacks LSTM has large computational demands on training and inference with complex models taking hours or days to run on specialized computers. LSTMs require huge historical data, hundreds of observations or thousands of observations, to be trained on. The black box nature has limited interpretability whereby explaining forecasts becomes a challenge and may pose problems in building trust within the organization. This implementation would need deep learning skills, which can be inaccessible to organizations incapable of data science.

ARIMA models can effectively and interpretably develop a forecast of products whose seasonal demand is not volatile. Training and prediction are computationally cheap, making it able to do quick predictions on large portfolios of products. The statistical basis results in explainable results- analysts will be able to know what historical trends are underlying the forecasts. ARIMA is a very useful standard to analyse complicated models and is also applicable to ordinary forecasting. Non-linear relationships as well as complicated interactions between variables are however difficult to utilize with ARIMA. The existence of the stationary time series requirement, requiring potentially information-causing preprocessing, and structural discontinuities in demand behaviour can significantly deteriorate the performance of the models.

Prophet is easy to use and does not need many parameters to be set, and it automatically uses missing data. Multiple seasonality patterns and effects of holidays can be represented well by the algorithm; thus, it is very suitable to business forecasting where known seasonal factors exist. The ability to deploy fast allows deployment of high numbers of product lines. Nevertheless, it is usually not as accurate as well-tuned ARIMA or LSTM models to predict the complex demand patterns. Prophet can work with trend and seasonality but can fail to pick up minor patterns that can be identified by more sophisticated machine learning techniques.

It is starting to be increasingly shown that hybrid models taking null and despotic aspects of various algorithms can provide the best possible outcomes. Hybrid LSTM-Prophet models displayed better results in the predictability of electricity demand, where Prophet plays the role of trend, whereas LSTM retrieves the pattern that is not linear and the result showed an RMSE of 65.34, MAPE of 7.3, and R2 of 0.98. The hybrid approaches mentioned above are similar and promising in the FMCG forecasting contexts. The complex concept of Nestle is the use of different models depending on product types and forecasting horizons, which is reflected in the fact that model choice is associated with trade-offs between accuracy, computational cost, implementation complexity, and interpretability: ideal trade-offs of different models may depend on application.

5.4 Implementation Problems and Success Factors.

Regardless of its impressive performance, serious issues of implementation arose in which organizations must manoeuvre through. Information quality and availability are also of significant impediments where AI models demand rich quality data. A significant number of FMCG firms find that information is tumbling in incompatible systems and is full of gaps and errors and does not reflect key external variables of weather and social media alerts. Nestle has spent much on data infrastructure preceding the introduction of AI models, having identified basic principles of garbage in, garbage out.

Other significant challenges are technical expertise gaps. The creation and maintenance of AI systems can only be done with specialized expertise gathered as data science, machine learning engineering, and knowledge of the supply chain domain. Nestle responded by cooperating with information technology manufacturers such as SAS Institute, Zest, and Schneider Electric as it developed internal competencies ecosystem through training facilities that promoted the implementation of NesGPTs.

It is technically complex to integrate with legacy Enterprise Resource Planning systems, Warehouse Management Systems and Manufacturing Execution Systems. The success of Nestle is an indication of high investment in system integration that allows the smooth flow of data between the AI platforms and the operational systems.

The management of organizational change is also as important as technical implementation. The AI necessitates alteration of a set workflow and decision-making. The workers who are used to the traditional forecasting might be reluctant to embrace the AI-based approaches that they do not know or do not trust. The case of Nestle and the creation of NesGPT and the training programs associated with it is an example of successful change management, where access to AI was democratized, and the company got comfortable with its use.

According to the experience of Nestle, critical factors of success include executive commitment to the dedication of resources and the vision, a basing building in data infrastructure preceding the implementation of models, incremental implementation with strategic pilots that prove the worth, effective change management through

comprehensive training initiatives, strategic collaboration with technology vendors and consultants, model diversity across applications as opposed to universal solutions, integration of AI and the knowledge of the human domain, continuous supervision and retraining of models, proactive data quality, as well as alignment with sustainability goals to support its stakeholders.

Sustainability-centered apps have special difficulties about scope 3 emissions tracking. These supply chain emissions are still hard to quantify since not all suppliers are data-mined, attribution is complicated in multi-tier supply chains, and no standard methods are in place. Studies have shown that Scope 3 emissions, which form up to 75 percent of company carbon footprints are the most challenging to monitor even with considerable rocks. Although AI enhances tracking, other issues inherent in the data availability are still evident in the industry.

5.5 Before And After Comparison: AI-Driven Decision Making At Nestlé

Aspect	Before AI Implementation	After AI Implementation
Forecasting Method	Traditional statistical methods relying on historical sales	AI & ML models (LSTM, Prophet, hybrid models)
Variables Considered	Limited variables such as past sales and seasonality	Hundreds of variables including weather, promotions, social media, economics
Forecast Accuracy	High forecasting errors	Approx. 30% reduction in forecasting errors
Decision-Making Speed	Slow and reactive	Real-time, proactive scenario analysis
Inventory Management	Overstocking or understocking	Optimized inventory positioning
Lost Sales (Stockouts)	Frequent stockouts	Up to 65% reduction in lost sales
Warehousing Costs	High holding costs	10–40% reduction in warehousing expenses
Waste Generation	High food waste levels	Significant waste reduction
Edible Food Waste	Often discarded surplus food	87% reduction in pilot factory
Waste Redistribution	Limited redistribution ability	Up to 700 tonnes redistributed (1.5 million meals)
Environmental Impact	High emissions and landfill waste	1,400 tonnes CO ₂ reduction
Quality Control	Late-stage defect detection	Early detection using computer vision
Production Stability	Unexpected failures causing spoilage	Predictive maintenance

CHAPTER 6: LIMITATIONS AND CONCLUSIONS

6.1 Summary of Findings

This research examined how AI-driven demand forecasting can reduce waste in FMCG supply chains, using Nestlé as a primary case study. The investigation yielded several key findings that highlight the transformative potential of AI technologies in addressing one of the industry's most pressing challenges.

First, AI-powered forecasting systems significantly outperform traditional methods. Evidence indicates that Nestlé achieved a 30% reduction in forecasting errors and up to an 87% reduction in specific categories of food waste. These improvements are largely due to AI's ability to process large and diverse data streams, capture non-linear demand patterns, adapt in real-time to changing conditions, and enable sophisticated scenario planning—capabilities that conventional spreadsheet-based approaches cannot match.

Second, the three primary machine learning models examined—Long Short-Term Memory (LSTM) networks, ARIMA, and Facebook's Prophet—each offer unique strengths and limitations. LSTM excels at modelling complex and volatile demand patterns but requires substantial computational resources and technical expertise. ARIMA provides efficient and interpretable forecasts for stable, seasonal demand, while Prophet allows for rapid deployment across multiple products, though sometimes at the cost of accuracy. Optimal model selection depends on factors such as product characteristics, forecast horizons, and organizational capabilities, with hybrid approaches showing promise for diverse FMCG portfolios.

Third, Nestlé's comprehensive AI implementation delivered measurable operational, financial, and environmental benefits. The Zest AI software pilot, for example, achieved an 87% reduction in edible food waste at one factory, potentially saving £14 million annually and avoiding 1,400 tonnes of CO₂ emissions. Beyond this pilot, improved forecasting enabled more effective inventory management, reduced overproduction, enhanced operational efficiency, and accelerated new product development timelines from three months to three weeks.

Fourth, despite these benefits, significant implementation challenges remain. These include data quality issues, gaps in technical expertise, complexities in integrating AI with legacy systems, organizational resistance to change, and substantial upfront costs. Successful organizations address these challenges through strong executive leadership, clear strategic planning, and a commitment to continuous training and process adaptation, foundation building before model deployment, incremental implementation through strategic pilots, robust change management programs, and strategic partnerships with technology vendors.

6.2 Limitations and Future Research Directions

This research has several limitations requiring consideration. Reliance on publicly available data rather than proprietary internal information may not capture complete implementation details or comprehensive financial impacts. Using Nestlé as the focal case study provides rich insights but limits generalizability to smaller FMCG companies or regional players with different scales and resources. The temporal focus on 2020-2025 captures recent developments but reflects the current state of rapidly evolving technologies requiring future updates.

Future research should pursue several promising directions. Longitudinal studies tracking AI implementations over 3-5+ years would reveal how benefits evolve and what long-term challenges emerge. Research examining how small and medium enterprise FMCG companies adopt AI technologies would address equity concerns and identify scalable implementation models. Comparative industry studies across different FMCG subsectors or comparing FMCG with other industries would reveal sector-specific success factors and transferable best practices.

Quantitative performance analysis accessing detailed operational data to analyse relationships between AI model characteristics, implementation approaches, and performance outcomes would strengthen evidence. Research developing and testing new hybrid forecasting models combining LSTM, ARIMA, Prophet, and other algorithms tailored to FMCG contexts could advance methodological capabilities. Finally, comprehensive lifecycle assessments quantifying total environmental benefits of AI-

driven supply chain optimization—including computational requirements and broader systemic effects—would provide complete sustainability pictures as AI deployments scale.

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