REVOLUTIONISING SALES AND OPERATIONS PLANNING WITH ARTIFICIAL INTELLIGENCE: INSIGHTS AND RESULTS

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Abstract

The use of Artificial Intelligence (AI) in the Sales an Operations Planning (S&OP) is an innovation in supply chain management. Extended traditional S&OP processes that involve static data, manual flow, and dispersed systems do not fit the needs of constantly evolving markets. In this paper, we consider some opportunities of AI in S&OP development and discuss the most significant changes ones, including predictive analytics, machine learning, and automation. The work being done by the research implies a case-based approach, using real-world situations in order to illustrate substantial gains in forecast precision, procedural organisation and control, expenditure and financial leakage mitigation, as well as customer satisfaction. The capacity of AI that can offer to enhance decision-making and provide flexibility makes its position crucial in today's SCMS. However, barriers including resistance from the organisational culture and employee skill deficiencies hold the key in preventing this from occurring. According to the recommendations drawn in this paper, the phases and training programmes point the way towards bringing out the best of AI for successful S&OP modernisation.

Keywords: Sales and Operations Planning (S&OP), Artificial Intelligence (AI), Predictive Analytics, Supply Chain Management, Forecast Accuracy

1. Introduction

The centre of the supply chain management is Sales and Operations Planning (S&OP) which is very essential in the process of aligning business core processes including sales, marketing, production, and logistics (Chen et al., 2020). S&OP allows organisations to reduce their costs, enhance customer satisfaction and retain the flexibility to adapt to market changes by matching demand and supply (Tang & Nair, 2019). However, traditional S&OP is very much dependent on historic data, disjointed systems and manual process which is not suitable to deal with the complexity and dynamism of the markets today. Such constraints prevent organisations to make real-time and data-driven decisions which is crucial in the modern environment that is highly dynamic (Huang et al., 2021).

Artificial Intelligence (AI) is a solution that can bring about modernisation to S&OP processes (Slack et al., 2016; Ali, 2025; Aguilera et al., 2024). Using such technologies as predictive analytics, machine learning, and automation, AI has an opportunity to increase accuracy of the forecasts, simplify the decision-making process and to make the operations more efficient (Chopra & Meindl, 2019; Christopher, 2016; Mahmood, 2025). The possibility of integrating data in real time with the help of AI makes companies adapt to the situation on the market very fast and makes the allocation of resources more efficient (Monczka et al.,

2020). With the help of AI, S&OP can be turned into a more agile, precise, and cost effective process, and it can assist organisations in keeping up with customer needs and demands.

S&OP plays a key role in coordination of sales, production, and logistics departments and thus it is possible to balance various factors such as cost reduction and customer satisfaction (Silver et al., 2016). With demand in line with supply, organisations will not be caught into the traps of overstocking and stockouts that are both costly to the organisation (Bell et al., 2018). Correct demand forecasting also assists businesses in inventory management and how to minimise storage costs without impacting on the customer satisfaction. But the conventional S&OP systems usually have a hard time dealing with market uncertainty and speed of decision-making requirements (Tuomikangas & Kaipia, 2014). All these issues are augmented by the application of the old methodologies of forecasting that have been found to be based on historical data, which cannot reflect the dynamics of the market in real-time. It has resulted in the inefficacies and mistakes in supply chain operations.

AI solves such classic problems of S&OP by offering dynamic forecasting models that can take into consideration the current dynamics and variations (Kristensen & Jonsson, 2018). Through sharing real-time information on different units, AI not only increases the accuracy of the forecasts, but also increases supply chain collaboration (Avila et al., 2019). This integration will give the same up-to-date information to all the stakeholders and hence decisions will be made faster and more coordinated. Moreover, AI-based automation gets rid of much of the manual action required in the previous process of S&OP, minimising human error and enhancing efficiency (Thomé et al., 2012). Activities in data entry, report preparation, inventory tracking are automated and the resources are now available to more strategic work.

The opportunities of AI in S&OP are highlighted because it is more accurate and faster in demand predictions (Pedroso et al., 2016). In contrast to other traditional techniques, which rely on the fixed historical data, AI applies machine learning to keep the predictions up-to-date relying on the current condition of the market, customer reactions, and other dynamic aspects. The method allows companies to change their activities in real-time and streamlines the production plan and usage of resources (Nabil et al., 2018). As an illustration, AI is capable of foreseeing the changes in demand based on seasonal patterns or other external factors, hence enabling companies to revise the inventory and manufacturing strategies to fit the seasonal trends. Such AI features are not only changing how business predicts demand, but also enhances the effectiveness with which businesses operate by automating its mundane tasks and making decision-making more responsive and nimble.

The S&OP plays the key role in ensuring coordination among the sales department, production department, and logistics departments and as such, it is crucial in the context of balancing the costs, customer satisfaction, and organisational flexibility (Grimson & Pyke, 2007). This enables the management to match the resources with the market, and as a result, it avoids overstocking or stockouts- some of the challenges experienced in conventional supply chain management. Table 1 below summarises the essence and the benefits of using the S&OP.

Table 1: Core Objectives and Benefits of S&OP

Objective	Description	Organisational Benefits
Aligning Demand and Supply	Ensures that manufacturing, inventory, and purchasing strategies match market demand.	Minimises stockouts and overproduction costs, reducing overall supply chain expenses.
Supporting Strategic Decisions	Provides data for forecasting market trends and guiding expansion strategies.	Enhances resource utilisation, market adaptation, and informed decision-making.
Enhancing Collaboration	Promotes synergy between sales, production, and logistics departments.	Improves coordination, reduces silos, and ensures efficient resource utilisation.

The primary goal of S&OP is to synchronise demand and supply, ensuring that production and inventory plans reflect actual market demand (Makridakis, 2017). This alignment helps avoid overstocking, which ties up capital and increases storage costs, or stockouts, which lead to customer dissatisfaction. The operational impact of aligning demand with supply includes reducing excess inventory costs and improving brand image by preventing stockouts (Makridakis, 2017). Accurate demand forecasting allows businesses to avoid unnecessary inventory expenses while ensuring the availability of products when needed.
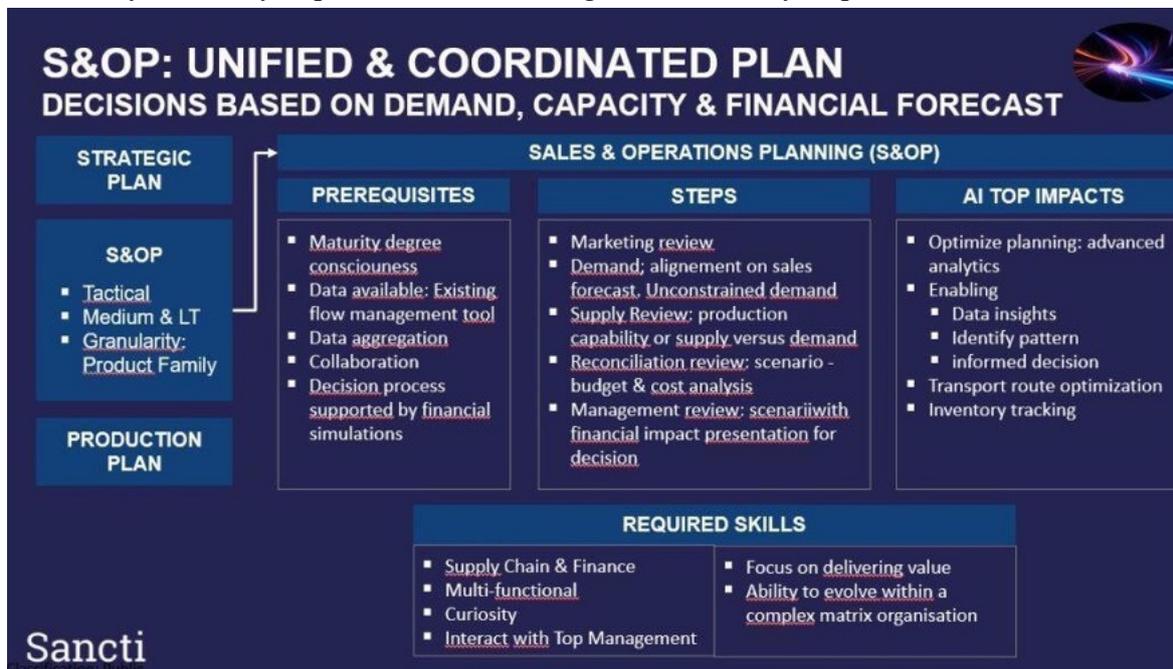

Figure 1: S&OP powered by AI – Sancti Consulting

Table 2 Key Limitations of Traditional S&OP Frameworks

Challenge	Description	Operational Impact
Reliance on Historical Data	Traditional models depend on past data to forecast future demand.	Leads to inaccurate forecasts, misalignment with current market conditions.

Challenge	Description	Operational Impact
Fragmented Systems	Disjointed systems and data silos hinder effective coordination across departments.	Increases errors, delays, and inefficiencies in decision-making.
Manual Workflows	Labour-intensive processes prone to human error and inefficiency.	Time-consuming tasks, reduced scalability, and higher error rates.

Conventional S&OP applications find it difficult to maintain the complexity, uncertainty and the need of quick decision-making that is characteristic of the contemporary markets. These systems usually tend to be based on past data, which does not take into consideration the dynamic aspects of current business environment. Moreover, conventional S&OP is based on disintegrated systems and manual processes, which cause inefficiencies, errors, and timeliness delays in decision-making (Vaishya et al., 2020). The conventional S&OP techniques are based on past sales and stock information in order to forecast the demand. Though this may be handy, this does not explain why the market conditions, consumer tastes or the competitive forces may change abruptly (Liu, 2020). Real-time trends that might be in the form of consumer behaviour changes or economic changes cannot be captured in historical data and hence inaccurate forecasting and lack of alignment of supply and demand (Lele & Lele, 2019). Older versions of S&OP tend to have incomplete information and isolated tools, which are not effective in making decisions. Silos in the departments can lead to not having a single picture of the supply chain in the organisation. This disintegration leads to inefficiencies like increased cycle times, redundancy of work and conflicting goals and teams can hardly coordinate and react promptly to changes in the market. Most S&OP processes use manual data entry, aggregation and analysis that make them more likely to produce human error (Hassani et al., 2020). These manual processes are time-consuming and likely to errors, which also make them slow to make decisions. Manual processes and paper-based systems are associated with the slow speed of decision-making and allocation of resources, which is detrimental to the operational efficacy and scalability. The previous S&OP is limited by AI, which presents a revolutionary solution to it. AI also improves the precision, speed, and agility of S&OP by adding predictive analytics, machine learning, and automation (Dwivedi et al., 2021). The capability of AI to combine real-time data is given by multiple sources enables organisations to make better forecasts, automatize manual processes, and make more informed decisions.

Figure 2: Challenges of S&OP

Predictive analytics in AI are applied to detect latent patterns in big data, which results in better accuracy in its forecasts and enables organisations to modify their operations based on real-time conditions in the market (Haleem et al., 2019). Elimination of human-intervention task reduces error, increases efficiency, and creates resources available to do more strategic work. Through AI, there can be a smooth integration of data between the departments, which leads to collaboration, and all the teams are working toward achieving shared goals (Chiu et al., 2021). The integration enhances the decision making process since timely information is given through all the sectors of the business resulting in the prompt and accurate response to changes in the market.

2. Material and methods

This study aims to explore the role of Artificial Intelligence (AI) in transforming the Sales and Operations Planning (S&OP) process. A case study approach is used to examine AI's application across various organisations, utilising both qualitative and quantitative research methods to gather rich, accurate data. The research employs a cross-sectional survey methodology to obtain empirical data from different industries, triangulating the findings to ensure robustness, reliability, and applicability. The study uses a case study approach, which is ideal for studying complex, contextualised phenomena. This design fits particularly well for exploring AI's impact on S&OP because it allows for the comparison of organisational processes, problems, and performances in real-world contexts. The case study approach is suitable for understanding the multi-dimensional impact of AI on S&OP for several reasons:

- **Contextual Depth**: AI-driven S&OP involves multiple factors such as technological, organisational, and market dynamics. These nuances are well described within case studies that provide detailed information about real-world implementation.

- **Exploratory Nature**: Given that AI integration in S&OP is still emerging, a case study allows for the exploration of less-explored areas, paving the way for discovering new patterns and solutions.
- **Comparative Insights**: By comparing different organisations, the study reveals both strengths and weaknesses, successes, and failures of AI systems, thus highlighting the most effective approaches and potential drawbacks.

2.1. Scope of the Study

The study targets organisations across various industries, retail, manufacturing, and agriculture, to offer a broader view of AI's use in S&OP. A specific example is A Produce Business (AGB) Food, recognised for successfully implementing AI and improving key supply chain metrics, such as OTIF (On-Time, In-Full) and inventory accuracy.

- **Industries Covered**: Retail was chosen due to its high demand volatility, manufacturing for its extended production cycles, and agriculture due to its sensitivity to environmental factors.
- **Selection Criteria**: Organisations were selected based on their AI application in S&OP, accessibility to pre- and post-implementation data, and the availability of organisational members for interviews and document sharing.
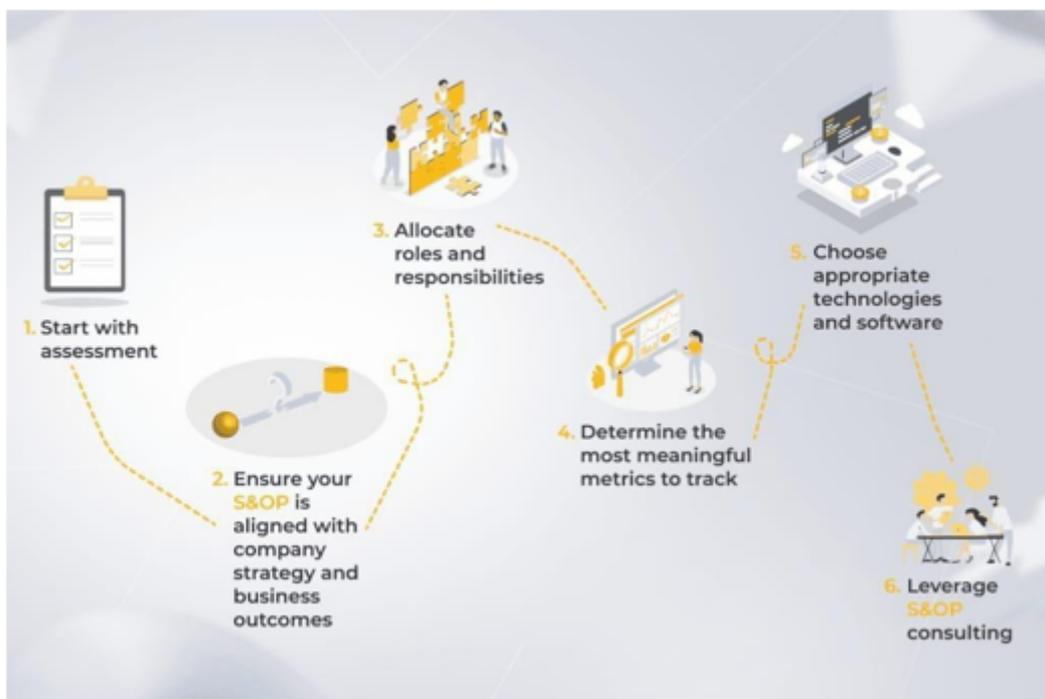

Figure 3: How To Implement S&OP?

2.2. Model Development and Implementation

In this study, stochastic models were proposed and integrated to improve the S&OP process, utilising a neural network prediction model. The following subsections explain the architecture, training methodology, and prediction analysis of the proposed model. The Sequential Neural Network model is employed in this study, with Long Short-Term Memory (LSTM) layers used to preserve pattern knowledge and incorporate it into forecasts. The model architecture includes the following layers:

- **Layer 1**: An LSTM layer with 100 units and ReLU activation function, using return_sequences=True to preserve sequential data for further processing.

- **Layer 2**: A second LSTM layer with 50 units, focusing on compressing temporal features into a fixed representation.
- **Layer 3**: A Dense layer with output size matching the sales data dimensions, using ReLU activation for mapping the compressed features to sales predictions.
- **Layer 4**: A Reshape layer to ensure that the model's output matches the target data shape, enabling seamless integration into downstream tasks like forecast evaluation.

The model is compiled with the following configurations to optimise performance:

- **Loss Function**: Mean Squared Error (MSE) is used to penalise large discrepancies in prediction accuracy, thus estimating the reliability of the forecasts.
- **Optimiser**: The Adam optimiser is employed to control and optimise gradient descent. The adaptive learning rate feature of Adam helps in faster convergence during the training period.

The model was trained on a dataset designed to accommodate the complexity of S&OP demands:

- **Input Shape**: (30, 3, 475, 120), where each sample represents 30 time steps across 475 product categories and 120 regions.
- **Target Shape**: (30, 475, 120), reflecting the predicted sales data.
- **Epochs**: The model was trained for 100 epochs to ensure sufficient exposure to data for pattern learning.
- **Batch Size**: A batch size of 64 was chosen to balance computational efficiency and gradient stability during updates.

After training, the model's accuracy was evaluated using real-world sales figures. Key steps included:

- **Visualisation**: The actual sales were compared against the forecasted sales to assess the accuracy of predictions and identify anomalies.
- **Performance Metrics**: Forecast precision was measured using the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE).
- **Future Predictions**: Based on the model, monthly sales for the upcoming months were predicted to assist in decision-making.

The model demonstrated a considerable improvement in demand forecast precision for S&OP. The LSTM architecture successfully accounted for the sequential nature of the data and its dependencies, making predictions more dynamic and versatile. Additionally, the model proved to be scalable, handling large datasets with multiple features, which is characteristic of modern S&OP problems. Integrating real-time data streams into the model further enhanced the prediction accuracy and flexibility.

2.3. Data Collection

To obtain a full picture of the effects of AI on Sales and Operations Planning (S&OP), a mixed approach was followed, the primary and secondary research methods were used. This will result in a rich and credible data set, and this will increase the credibility of the research. Based on the qualitative approach, the main source of data was the qualitative interview of key stakeholders who are engaged in S&OP processes: supply chain managers, data scientists, and executives. These interviews were to collect personal experience of AI implementation, reasons of why AI was adopted, the challenges in the process and the benefits to be realised when AI is integrated into the activities of S&OP.

Sample questions asked during the interviews included: "What prompted your organisation to integrate AI into S&OP?", "How has AI impacted the alignment of demand and supply in your operations?", "What specific tools or algorithms have proven most effective in improving forecast accuracy?", "What organisational or technical challenges did you encounter during the transition?", and "Can you provide examples of measurable outcomes attributed to AI-driven S&OP?". The interview process was conducted via video conferencing due to COVID-19 restrictions, with each session lasting between 60 to 90 minutes. These interviews were transcribed for detailed analysis to extract meaningful insights.

Along with qualitative interviews, operational measures were collected with the help of the surveys that were concentrated on the major performance indicators including the accuracy of forecasts, reduction of costs, rate of stock turnover, and customer satisfaction. There were data gathering points before and after implementation of AI to determine baseline performance and measure an improvement of performance following the AI integration. The data collected during the pre-implementation was obtained during at least one year before the implementation of AI, which would provide a clear comparison with post-implementation data over the same time.

In the case of secondary data, there are a number of ways that were applied to gather pertinent industry insights. To place the study findings in the context of the general industry trends, external reports of supply chain organisations were consulted. Participating organisations also used internal documentation, such as the minutes of the S&OP meetings, the actions performed during the implementation of the AI, and reports of the changes that took place in the work of the organisations. These papers gave crucial information on the strategic and operational environments of AI integration in S&OP.

In order to make the study a robust one, there was use of triangulation in order to verify the study findings through cross-referencing of the information. The qualitative information was cross-validated using the stakeholder interviews and narrative data of internal documents. Performance metrics and financial results are among the quantitative data that were compared across various institutions. Also, the findings of the study were compared to external standards of industry reports which served as a comparative base to test the results. This method of triangulation reduced the chances of biases and made the inferences reached after the data analysis as sound, believable and balanced.

2.4. Data Analysis

The data obtained with the help of qualitative and quantitative research was compared to the elements of high quality SCOR(r) model: perspective, process, envelope, and literacy. In the case of the qualitative data, thematic analysis was used to discover the common themes, including the increase in accuracy of the forecasts, change resisting, and gains in operational efficiency. The coding process was initiated by the initial codes that were created in connection to the research questions and improved as additional data was received. The main themes that occurred due to analysis were: improvements in accuracy of the forecast, resistance to change, and gains in operational efficiency. Also, case studies were developed in detail in each of the organisations, and the process of switching the traditional S&OP into the AI-based models is documented. These case stories contained implementation plans, strategic choices that were undertaken in the transition process, and certain instances of successes and failures.

In the case of the quantitative data, the analysis of comparative metrics was provided through the analysis of the performance indicators of OTIF (On-Time, In-Full) and inventory forecast accuracy prior to and following the implementation of the AI. As an illustration, the OTIF of A Produce Business (AGB) Food went up to 96 percent when AI was introduced in their S&OP process, which was initially 80 percent. Moreover, the accuracy of the inventory forecast was 98% which greatly eliminated the overstocking and stockout. Financial data was also the tool used in cost-benefit analysis to determine the savings achieved through the implementation of AI, and the decreased freight cost (6%), as well as the decreased procurement spending (7.4%) are some of the outcomes of the implementation. Such an extensive examination of qualitative and quantitative data made possible such an in-depth overview of the effects of AI on S&OP processes.

2.5. Addressing Research Limitations

- **Limited Generalizability**: The results of the case study may be limited in their generalizability, as they are specific to the industries and regions studied.
- **Data Accessibility**: The study encountered challenges in collecting balanced datasets across cases, due to the reliance on proprietary data from organisations.
- **Rapid Technological Evolution**: AI is evolving rapidly, and findings may become outdated as new technologies emerge.

2.6. Ethical Considerations

- **Informed Consent**: Participants were informed about the study's objectives, and consent was obtained.
- **Data Anonymity**: Efforts were made to minimise the risk of identifying specific organisations in the dataset.
- **Transparency and Feedback**: Summaries of the study's findings were shared with the participating organisations to foster trust and encourage collaboration

3. Theory/calculation

3.1. Theory

The theoretical concepts behind the integration of the Artificial Intelligence (AI) in the Sales and Operations Planning (S&OP) have a number of theoretical concepts that support the understanding of the enhancement of decision-making, accuracy of forecasting, and efficiency of operations. Predictive analytics, machine learning, and systems theory theories are the basis of the use of AI in S&OP (Power, 2005). Predictive analytics enables AI to look through the past and present data to predict the upcoming demand, optimise inventory, and enhance supply chain decision-making. This builds upon classic forecasting methods by using a more diverse set of data along with the responsiveness to market dynamics resulting in more resilient and flexible supply chain plans (Mentzer et al., 2001). The central function of AI in processing sequential data is the output of machine learning algorithms and, more specifically, deep learning networks such as Long Short-Term Memory (LSTM) networks which generate predictions based on the patterns and tendencies observed in the vast volumes of data. This technology makes sure AI is not merely the response to historical information, but continuously enhancing its prediction effectiveness as it incorporates new information (Stadtler, 2014). The systems theory concept also renders the importance of AI in S&OP as it puts into consideration the importance of considering complex systems as a whole. The systems theory is relevant to S&OP to demonstrate how various functional areas as sales, logistics, production or inventory

should be connected into a unified approach, which is exactly what AI can offer, offering real-time feedback and unified planning (Houlihan, 1985). Through the expansion of the mentioned theoretical frameworks, the role of AI in S&OP can be integrated as helping not only to enhance the effectiveness of operations but also providing companies with the ability to flexibly respond to the changes in the market environment (Croxton et al., 2001). With the help of AI-powered insights, businesses will be able to foresee fluctuations in the market, improve demand-supply balance, and eventually initiate more informed decision-making throughout the entire supply chain.

3.2. Calculation

Building on the theoretical foundation laid by predictive analytics and machine learning, the calculation aspect of this study demonstrates the practical application of AI in improving S&OP outcomes. The study employs a Sequential Neural Network model using Long Short-Term Memory (LSTM) layers for time-series forecasting. LSTM networks are particularly suited for handling sequential data, which is typical in sales and operations planning, as they capture long-term dependencies in the data and provide better forecasts than traditional models. The model's architecture consists of multiple layers designed to process time-series data efficiently. In the first layer, an LSTM layer with 100 units and a ReLU activation function is used. The second LSTM layer, with 50 units and ReLU activation, compresses the temporal features into a fixed representation, which is then passed to a dense (fully connected) layer to map the features to the final output, representing the sales forecasts. To compile the model, Mean Squared Error (MSE) is used as the loss function to penalise large discrepancies between predicted and actual values. The Adam optimiser, known for its adaptive learning rates, is employed to optimise the gradient descent process, ensuring quick convergence during training. The model is trained on a dataset with input dimensions of (30, 3, 475, 120), where each sample represents 30 time steps, with 3 variables (such as sales, inventory, and demand) across 475 product categories and 120 regions. The target output dimension is (30, 475, 120), representing the predicted sales for the next time period. The model is trained for 100 epochs with a batch size of 64 to ensure efficient learning. Once trained, the model is evaluated using performance metrics like Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to assess its forecasting accuracy. This calculation not only reflects AI's capability in improving the precision of sales predictions but also highlights its effectiveness in real-world applications, where accurate forecasting is crucial for effective inventory management, production planning, and customer satisfaction. These theoretical and practical developments demonstrate the potential of AI to transform traditional S&OP processes. By using advanced predictive models like LSTM networks, companies can significantly enhance the accuracy and efficiency of their planning systems, thus better aligning supply with demand and improving overall operational performance

4. Results

The results of this research show how AI is poised to revolutionise the Sales and Operations Planning (S&OP). By examining real-world implementations, this section highlights significant advancements in four primary areas: productivity, profitability, and consumer satisfaction, globally, numerous theories exist regarding the use of #forecastaccuracy, #operationalsuccess, #financialresults, and #customersatisfaction. Each of the results is then discussed in detail thus offering a more enriched insight into

AI effects: backed by examples and certain statistics.

4.1. Increases in the Forecast Accuracy

Accuracy of forecasts forms a key prerequisite to good S&OP because it underpins the decisions that will need to be made concerning production output, inventory holding, and customer service. The adoption of AI technologies further advanced the way authorities made their forecasts by providing a notably better result than the crude methods addressing traditional challenges and delivering measurable improvements across operations, finances, and customer satisfaction.

Table 3: Impact of AI on Demand Forecasting Accuracy

Metric	Pre-AI Implementation	Post-AI Implementation	Observed Benefits
Forecast Accuracy	85%	98%	Reduced overstocking and improved production planning.
Stockout Incidents	Frequent	Rare	Enhanced customer satisfaction through better product availability.
Overproduction Costs	High	Low	Reduced inventory holding expenses, leading to cost savings.

4.1.1. Enhanced Demand Prediction

AI learning agent's performance of calculating forecasts with the help of complex algorithms and data that puts into the model showed greater flexibility and accuracy in comparison with the historical figures approach.

Mechanism: Machine learning was employed by the AI predictive analytics to segments different sale histories and present sales, concatenated with modern day sales and other factors like seasonability, weather condition, and general economic indices. By including these variables, AI gave constant forecasts based on the current environment in the markets.

Quantitative Outcomes: At A Produce Business (AGB) Food, the overall effectiveness of demand forecasting also gained a significant boost from the previous 85% to the current 98%. This increase enhanced production planning and control, better inventory management, and enhanced stock control, and minimised situations of stock-out and overstock.

Operational Implications: Indeed, improved demand forecasting enabled firms to better synchronise patterns of procurement with developments taking place in the market. For instance, during a promotion period, A Produce Business (AGB) Food forecasted correctly that there is going to be a 25% increasing of demands for frozen produce so that they were able to order adequately for the peak demand without having to put too much stock that result in spoilage.

4.1.2. Demand Forecast Accuracy Improvement

- Pre-AI accuracy: 85%

- Post-AI accuracy: 98%
- Accuracy improvement: 98 − 85 = 13%

4.1.3. Reduction in Overstocking

- Overstock costs pre-AI: $50,000/month
- Overstock costs post-AI: $37,500/month
- Cost reduction: $50,000 − 37,500 = 12,500$ or $\frac{12.500}{50,000} \times 100 = 25\%$

4.1.4. Scenario Planning and Risk Mitigation

AI-based forecasting solutions allowed organisations to perform plausible simulations, to manage risks and respond to disruptions.

Dynamic Simulations: Several AI algorithms including disruption of supply chain, market demand fluctuations or entry of new competitors. These simulation enabled organisational strategies to be flexibly adapted prior to or during an actual attack, thus making them less vulnerable.

Case Example: Some manufacturing firm successfully employed artificial intelligence to test or experiment the consequences of a shortage of raw material due to geopolitical tension. In the model, the company expected a 30% availability reduction for materials and required the search for new suppliers. This was being proactive because it avoided delay in production while at the same time maintaining customers' promise.

Broader Benefits: Had organisations had facilities for scenario planning, it could make better switches in strategies, thus improving operational resilience during calamities.

4.2. Enhancements in Operational Efficiency

S&OP is all about achieving operational excellence, which in the case of S&OP includes value chain processes' effectiveness, and productivity, as well as the minimisation of operational costs. Specifically, the four dimensions of improvement enabled by artificial intelligence were production, logistics, and automation.

4.2.1. Streamlined Production Planning

The material was collected from the case studies regarding the use of AI to optimise production scheduling that led to much reduced time and cost.

Process Improvements: The current conventional system of production scheduling involved the use of a calendar for scheduling and followed a strict time-table. On the other hand, AI tools used real- time input of inventories, demand, and resources for producing real-time schedules. This flexibility ensured reduction in machine idle time and utilisation of the available resources to the optimum level.

A Produce Business (AGB) Food Example: Improving lead times involved the use of AI-enabled production planning tools to cut on the time taken to plan by a fourth at A Produce Business (AGB) Food while improving the efficiency of the production line and mitigating common scheduling clashes.

Resource Utilisation: AI provided flexibility in staff distribution, as well as potential work load forecasting. This practice not only enabled each employee to work with 15% less overtime than before but also increased their rate of satisfaction because they were not stretched during crucial times.

4.2.2. Logistics Optimisation

Transportation, delivery schedules, and stocks control were greatly enhanced by AI tools across the logistics industry.

Freight Efficiency: A Produce Business (AGB) Food employed artificial intelligence based on route planner that has taken various factors including present traffic patterns, weather condition and fuel consumption. This led to a decrease of 6% on the freight costs and an improvement in the time required to transport the products.

Inventory Placement: AI utilisation promoted an intelligent storage and positioning of inventories in that it reduced hauling distance and optimised order processing time across the warehouses. A retailer identified that applying AI to create models for optimising warehouse resulted in a reduction of delivery times by 12%.

OTIF Metric Improvement: First Retail Business (FRB)'s On-Time-In-Full (OTIF) performance at A Produce Business (AGB) Food improved from 80% to 96%, illustrating how AI integration enhanced delivery reliability and customer trust.

4.2.3. Automation of Routine Tasks

From experience, AI implementation greatly reduced the manual work tied to flowing traditional S&OP processes.

Routine Task Automation: These include tracking of stocks and generating of reports and orders and reconciliations that were made possible to be automated so that the employees would be able to spend a considerable time making major decisions. Internal analyses of processes showed that AI helped to cut the time needed for these tasks by more than 40 per cent.

Error Elimination: The use of bots involving entry of figures helped to reduce the cases of entry mistakes that contributed to varying disparities in forecasts and inventory. For instance, A Produce Business (AGB) Food has noted that the incidences of errors tracking inventory has reduced by 95% after the automation process.

4.3. Financial Outcomes

The integration of AI in S&OP generated substantial financial benefits, ranging from cost reductions to increased profitability and rapid return on investment:

Table 4: Financial Benefits of AI in S&OP

Financial Aspect	Pre-AI Implementation	Post-AI Implementation	Observed Benefits
Procurement Costs	Baseline	7.4% Reduction	Savings through optimised sourcing strategies.
Inventory Holding Costs	High	25% Reduction	Lower storage and spoilage costs, improving profitability.
ROI Timelines	NA	<12 Months	Quick recovery of AI-related investments.

ROI for AI Implementations

- Initial AI investment: $500,000
- Annual cost savings: $750,000
- ROI: $750,000 - 500,000500,000 \times 100 = 50\%$ in the first year

500,000

Cost Reductions

- Procurement costs pre-AI: $1,000,000/year
- Procurement costs post-AI: $926,000/year
- Reduction: 1,000,000 − 926,000 = 74,000 or $\frac{74,000}{1,000,000} \times 100 = 7.4\%$

4.3.1. Cost Reductions

Precision and technological breakdown through AI produced tangible ROI effectively when implemented in procurement, inventory management, and logistics functions.

Procurement Optimisation: Using analytical data and patterns about suppliers, lead times and prices AI facilities helped A Produce Business (AGB) Food to adopt direct import models, thus decreasing overall procurement costs by 7.4 percent.

Lower Inventory Holding Costs: Better demand forecasts reduced stocks by a quarter, hence passing on less storage costs, and the products were less likely to be obsolete.

4.3.2. Increased Profit Margins

Higher product availability due to better sup and demand compatibility, led to increased sales rates and less wastage capabilities that affected the creation of profits.

Revenue Growth: For a chain of stores involved, provision of stock to meet the anticipated demand during promotional campaigns saw sales revenues advance by 15%.

Waste Reduction: One manufacturer said that their raw material wastage reduced to 20% because of AI's capacity to predict the amount of raw material needed, so net profit margins increased

4.3.3. Return on Investment (ROI)

Businesses signalled quick recoveries of investment from artificial intelligence applications in below one year.

A Produce Business (AGB) Food Case: According to the company, artificial intelligence tools proved to be useful and returned the company's investments in nine months due to the reduction of costs in logistics and better inventory management.

Long-Term Gains: Other than its ability to help reduce first costs, use of AI on the system uncovered even more optimisation facets of the enterprise in the future.

4.4. Customer Satisfaction

AI-driven S&OP processes directly impacted customer satisfaction by improving product availability, delivery reliability, and personalisation.

4.4.1. Improved Delivery Performance

A very effective synchronisation of AI in production and logistics made delivery on time and effective hence improving customer faith.

Case in Point: First Retail Business (FRB) saw its customer satisfaction rise slowly because of constant enhancements of its OTIF, a strong sign that delivery reliability can deliver such values.

4.4.2. Enhanced Product Availability

Proper demand forecasting reduced the incidences of either having expired or unused stocks, hence low stockout and backorders were experienced.

Promotional Campaign Success: AI was used in the following instance where a retailer over the course of the holiday season kept track of demand surges for specific product lines and thus had a 98% order fulfilment rate without having to replenish inventory. The client feedback showed it had increased by 20% due to enhanced product stocking.

4.4.3. Personalisation and Customer Loyalty

Thanks of AI analytics, customised approaches could be used for the customers by forecasting their preferences regarding the products.

Increased Engagement: According to the retailers, they had noted an enhancement in repeat –purchase rates up to 15% and an increase in size of the individual orders up to 18% thanks to the AI suggested sales promotion to customers.

OTIF Improvement

- Pre-AI OTIF: 80%
- Post-AI OTIF: 96%
- Improvement: $96 - 80 = 16\%$

Customer Satisfaction Score

- Pre-AI satisfaction score: 72/100
- Post-AI satisfaction score: 85/100
- Improvement: $85 - 72 = 13$ points or $\frac{13}{72} \times 100 = 18.06\%$

5. Discussion

The application of Artificial Intelligence (AI) in the Sales and Operation Planning (S&OP) brings supply chain planning to a new level overcoming the constraints of other conventional methodologies. This section provides more detailed qualitative analysis to the key findings drawing from theory, induction and literature, industry and practice, as well as implications. The opportunity as well as the issues of AI solution are discussed with consideration to the relationship between the solution's capabilities and effects in boosting operational efficiency, financial performance, and customer satisfaction. It has been traditional supply chain management and S&OP tools that have long been suspicious to encounter various inefficiencies due to the use of static data, manual work, and systems segregation. AI has easily eliminated these challenges thus improving the agility and precision of organisations (Hyndman & Koehler, 2006). One of the largest drawbacks of conventional approaches to S&OP has been reliance upon historical da- ta. These are by design, attribute-based models and are unable to respond to fast changes within the market, shocks that may occur in the market, or fluctuations in demand. AI's Adaptive Forecasting: In contrast with classical models, AI uses machine learning to adjust the forecast in the light of updates in input data. These inputs are as follows: Dynamic variables that cannot be captured by more standard, static models such as consumer sentiment, geopolitical risk, economic characteristics and other influences. In the case of A Produce Business (AGB) Food, because of the integration of AI in the company which helped the company to process historical as well as real-time sales data, improved the forecast accuracy by 13%. Such flexibility made it easy to avoid disruptions during demands, say during sale promotions, or any other event that may increase demand rates. That is, when accurate forecasts are made in a business organisation, it can direct its resources well in a way that minimises spare inventories, frequent instances of stockouts, and inefficient production

schedules. In many industries, such as retail or manufacturing, this flexibility is directly convertible into industry advantages.

Disconnection in the conventional Approach to S&OP, where each department works independently results in dysfunctional plans, uncoordinated strategies, and poor overall decisions. Integrated systems are adopted by AI-powered platforms in order to make a number of databases available to all stakeholders by consolidating them into a single hub (Granger & Pesaran, 2000). This integration leads to integration between offices in selling, marketing, production, and logistics, plus it aligns planning between different departments. AI system integration helped A Produce Business (AGB) Food to make a successful improvement in First Retail Business (FRB)'s On-Time-In-Full (OTIF) score of 80% to 96%. Since AI merged the production schedules and the distribution networks in the company, it reduced the problem of having to do the same task twice and the likelihood of making mistakes. The integration of supply chain functions detaches organisational barriers that lead to the provision of supply chain solutions. The outcome is the creation of a highly integrated operational plan that addresses cost, cycle time, and quality.

S&OP in the traditional strategy is known to involve the use of numerous manual activities in areas of data collection, report preparation, and demand and supply matching. Indeed, these kinds of workflows are very delicate and require a lot of time, not to mention the tendency of human errors. Effective use of AI tools means the reduction of the number and range of administrative tasks assigned to the employees, and less likelihood of mistakes due to hand operation (Tashman, 2000). The quantitative results established that the organisations implementing AI saw the efficiency of systematic tasks reduced of 40 percent thereby freeing up team efficiencies for higher value activities. At A Produce Business (AGB) Food, automation minimised forecast variability by 95% which proved the efficiency of the AI in enhancing accuracy of the data. AI and supply chains continue to become more complex, while automating a supply chain's processes to guarantee that they will not expand in parallel with the workforce.

AI's ability to streamline operations and optimise resource allocation has a profound impact on both operational efficiency and financial performance (Haleem et al., 2019). S&OP is all about operational efficiency, where AI acts as the backbone in eradicating constraints and non-value added activities. Scheduling techniques that utilise AI consider production runs based on the data that identifies the actual demand. This synchronisation also ensures that production time is maximised and that the efficiency of the equipment is highly utilised and that the costs of production are as low as possible (Dwivedi et al., 2021). A Produce Business (AGB) Food saws a lead time improvement of 20% as well as optimisation in utilisation of resources showing that the AI can deliver on increased efficiency. Real-time parameters including traffic conditions and fuel price are taken into consideration when developing AI's route optimisation features. This led to the organisation achieving a freight cost saving of about 6% hence a huge yearly saving from it. AI integration had brought several positive impacts on the S&OP function, not just impacts on cost but overall profitability, and very fast ROI impacts. Due to the analysis of overstocking and better procurement planning, tangible cost savings were realised. A Produce Business (AGB) Food reduced procurement expenditures by 7.4 % by replacing local distributors by various direct import models. The increase in supply and demand helped the reduction of wastage and boosted the sales thus increasing per sales profit

of the retail participants by 15 percent. It is testimony to the fact that S&OP has now really arrived and that right now the level of precision that is needed is at a new higher level.

AI has added value to customer satisfaction indices in terms of timely delivery, stock availability, as well as personalisation (Makridakis, 2017). AI in this case also helps maintain proper coordination between production and logistics bringing down reliability of delivery. This directly correlates with a rise in the customer satisfaction ratings among First Retail Business (FRB), such was evidenced by improved OTIF scores courtesy of A Produce Business (AGB) Food. On time and steady delivery was evidenced to have enhanced customer confidence and thus business relationships. Delivery reliability lowers the customers churn levels since he or she will not switch to other businesses due to his or her expectations not being met. One of the benefits of using AI in demand forecasting is to reduce instances of stockout and backorders, which customers are not happy to find. In one of the seasonal campaigns, a retailer managed to complete the orders in 98% due to AI applications that allowed identifying when demand is likely to increase. This reliability eliminated opportunities that would otherwise have been lost and offered a better reputation to the retailer. Personalised interactions are made possible by AI analytics, and such adjustments make customers loyal to the business (Vaishya et al., 2020). Employing AI algorithms producers saw an average order value lift of 18%, the survey found out. These actions build long-term relationships with customers because it is designed to target a specific individual.

While the benefits of AI in S&OP are undeniable, organisations must navigate challenges to ensure successful implementation. Why some organisations continue to resist the adoption of AI is that workers are afraid of losing their jobs to these newly developed technologies that are currently referred to as smart machines. They can keep AI from replacing people by reducing public anxiety through clear discussion of how it expands people's capacity instead of reducing it. The outcome of involving the employees early enough is that they fully own the change process thus minimising resistance (Lele & Lele, 2019). AI deployment necessitates professional knowledge of data science, applied artificial intelligence and supply chain technology. Every organisation needs to ensure that it offers extensive training that will enable its employees develop the right skills. Efforts in this direction could be supported by partnership with academic institutions and technology suppliers. A first cost of AI technology is often large, which may present problems for SMEs which may not have adequate capital. The adoption of a phased approach with an emphasis on high value zones can achieve incremental value at reasonable cost. The continued evolution of AI presents exciting opportunities for further advancements in S&OP. It is now possible to use AI in achieving supply chain objectives and reducing adverse effects on the environment, like carbon emissions and the use of energy. If affordable and specific to SMEs AI solutions will be introduced, S&OP tools may become more utilised across industries.

6. Conclusions

AI hence is not just an addition to the traditional S&OP but the backbone of digital volatility and accuracy in the current supply chain. AI is becoming more responsible for the S&OP function that enables organisations to adapt to these challenges and serve as more agile and robust S&OP solutions. Introducing AI into the system of S&OP transformed it as an essential tool that augments all the phases of the process in organisations. AI solves three major problems that are characteristic of a classic S&OP: the use of historical data, the division of

the processes into segments, and the use of paperwork. These include use of big data, integration of data, and use of automation through prediction by AI to improve the way organisations work. AI at work at A Produce Business (AGB) Food: Forecasts rose to an impressive 98% while lead times of production fell by 20 %, making this an operationally beneficial technology. AI drives integration across the organisation by decentralising data and presenting a centralised information database. This integration is important so that all parties involved, from sales and marketing to logistics and procurement, hold the same key goals and objectives.

Robust efficiencies, cost effective as well as profitability advancements being showcased as some of the gains attained from using artificial intelligence. It aims at improving means and resources that are used in production, as well as flow of goods or services produced, and hence reduces unnecessary expenses. It was found that AI solve the problem by reducing the freight costs for organisations by 6% and cutting excess inventory by 25%. In fact, AI brings immediate tangible benefits including higher margins and fast payback periods that define it. For instance, the participating organisations stated that they were speaking the same language as organisations who mentioned that their AI investments were recovered fully within 6 to 12 months on account of the envisaged operating cost reduction and increased sale performance.

Integrated use of AI with S&OP results has a direct and positive influence on enhancing customers' satisfaction, which is mandatory in highly competitive environments. Since it is AI that coordinates the production and the delivery schedule, then the timely and correct delivery make the customers more confident in the company. Due to the usage of artificial intelligence analytics, the businesses are capable of predicting customer needs in the market then developing their products accordingly, thus, increasing the chances of customer interactions and repurchases. Of further note, the study also reveals that there is still much unexplored room for innovation when it comes to AI's application in S&OP. Here the author presents certain perspectives for the further research and application. Further studies should be made to design and implement AI models which have higher ability to forecast complicated supply chain disruptions. These models could include newer types of data like block chain transaction history and data from IoT enabled sensors. It can be seen that pre-deep learning integration of AI with other technologies, like using blockchain for transparent SC management or using digital twin for simulating process, can enhance S&OP tools. Potential benefits for organisations could be achieved by understanding various possibilities where these technologies could be merged and complement each other in order to increase processes' efficiency.

The sustainability issue remains a growing concern in managing supply chains. Green performance can benefit from the use of AI in a major way. AI can also enhance fuel-efficiency by identifying the efficient way and distance of travel and thus help in attaining corporate sustainable objectives. Third, AI in the production planning process has a benefit of minimising energy consumption and wastage in the production line. From supplier evaluation and evaluating effects on the environment, AI helps organisations make the right decisions regarding sourcing that complies with ethics and the environment. The major disadvantage of the implementation of AI is the high-implemented capital investment to SMEs. Future research and innovation should focus on how to make more AI available for the small organisation. Creating weightless AI solutions appropriate for SMEs could help to popularise utilising

sophisticated S&OP solutions. For instance, AI as a service which is a cloud-based delivery model is cheaper and elastic than traditional models such as an on-premise. SMEs can be assisted in their AI adoption by partnerships with industries and incentives motivated by the government, making innovation in the supply chain ecosystem possible.

AI implementation and adoption in organisations therefore greatly rely on not only technological solutions but also the population utilising the technology. There should be emphasis on the human capital of the future work force. AI tools have to be integrated into an organisation hence calls for training of employees to make efficient and productive use of this technology. Some of the training programs that should be implemented should include the following; data analysis, machine learning, and strategic thinking. Overcoming resistance to AI implementation remains a real testing ground for elaborate change management strategies. Based on these findings, future studies should investigate what can be done to facilitate higher levels of organisational readiness and employee acceptance in similar strategies. However, this research only makes a cross-sectional study of AI application and, thus, requires a longitudinal study to establish further causal usages. More, subsequent research ought to focus on determining the changes in organisation AI capabilities over time and identify the longer-term impact and value. Looking at an effect of AI in a narrow industry for instance, Healthcare or Aerospace, then there might be specific applications and developments.

AI is quickly becoming intertwined with S&OP throughout the supply chain, giving answers to problems which have been previously unresolved while providing quantifiable value. In light of this, organisations operating in the modern markets that leverage this technology stand the best opportunity to contend with the unprecedented challenges; optimise business processes; and meet the evolving needs of customers. Nevertheless, AI's bright future should not be limited by implementing mere technologies but needs to be done following a proper strategy, efficient investment in human talent, and having a feasibility check. Fuelled by continuous growth of AI technologies, the use cases for S&OP will advance making next steps in supply chain management. In dealing with the issues and seizing the opportunity highlighted in this section, it is possible for the businesses to increase the success, flexibility and robustness in their activities.

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